Working part-time and full-time and body weight in old age: effects and mechanisms

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Abstract

Increasing populations of older people participate in the labor market due to improved life expectancy. Many of the older workers engage in part-time work after holding career jobs. Taking an instrumental variable approach, we investigate the causal effects of working part-time and full-time instead of retirement on body weight in old age. We find that both working part-time and full-time reduce body weight, but working part-time has a much larger effect. The findings are most pronounced for women and high income earners. We analyze time use data to investigate the potential mechanism. We find that while working part-time, women and high income earners spend substantially less time on two activities that demand the least amount of metabolic energy when compared to all other activities: watching television and sleeping.

JEL codes: I12, J14, J21, J26
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1 Introduction

The labor force participation rates of older workers at any given age is increasing in the United States, as in many other industrialized countries, due to population aging. According to the Bureau of Labor Statistics, between 2010 and 2020, labor force participation rates of the workers between the ages of 25 and 54 will decrease by 0.9 percentage points, while those of the workers aged 55 and over will increase by 2.8 percentage points. On the other hand, today older workers spend more years in the labor market due to the increase in the statutory retirement age that will reach 67 by 2027. These empirical accounts show that working has become more common in old age. On the other hand, an integral part of the well-being in old age is health. Since health conditions tend to deteriorate throughout the old age, it has become important to investigate how work and health interact in old age. In fact, a growing body of literature is analyzing the effects of retirement on the physical and mental health conditions of older people.

Among other health problems, obesity is a leading health problem in the United States. A substantial fraction of the population is overweight or obese. Flegal et al. (2010) show that, among those aged 60 or older, from 1999–2000 to 2007–2008, obesity increased from 31.8 percent to 37.1 percent for men, although it decreased from 35.0 percent to 33.6 percent for women in the National Health and Nutrition Examination Survey. Obesity is considered to be a main cause of a range of other serious health problems. Must et al. (1992), Blair and Brodney (1999), and Janssen (2007) show that overweight and obesity are related to morbidity. Haslam and James (2005) argue that overweight and obesity considerably increase the risks of cardiovascular disease, diabetes, and cancer. A number of studies investigated the causal effect of retirement or working part-time on body weight. Chung et al. (2009) find that retirement leads to modest weight gain in the United States. Godard (2016) finds that retirement increases the probability of being obese among men in Europe. Au and Hollingsworth (2011) find that women working fewer hours are less likely to gain weight in Australia.

Our study aims to extend the scope of the studies analysing the effect of labor market participation on body weight, but it also aims to contribute to the literature on the health effects of labor market participation in general, in two important respects. First, we distinguish between working part-time and full-time, and analyze their effects on body weight among the elderly. The majority of the previous studies on the health outcomes of retirement compare the health outcomes of those who are fully retired to the health outcomes of those who are working any positive number of hours, not distinguishing part-time from full-time work. The main studies of this literature are the following. Coe and Zamarro (2011) and Insler (2014) consider overall health in Europe and the United States. Eibich (2015) consider self-perceived physical and mental health in Germany. Bonsang et al. (2012), Charles (2004), Coe and Zamarro (2011), Mazzonna and Peracchi (2012, 2016), and Rohwedder and Willis (2010) consider cognitive abilities and depression in the United States and Europe. Hallberg et al. (2015) and Biró (2016) consider inpatient and outpatient care in Europe and the United States.

Few studies have analyzed how the actual number of hours worked influences the health conditions of those who still work. Vaus et al. (2007) find that people who made a gradual transition to retirement by decreasing work commitment over time report better overall health compared to people who made an abrupt transition into retirement in Australia. Forbes et al. (2015) find that people who work part-time later in life report better mental health compared to people who are retired in Australia. Dave et al. (2008) find that people who are partially retired have better physical and mental health outcomes than people who are fully retired, but both groups are worse off compared to those who work full-time in the United States. On the contrary, Neuman (2008) finds that not only retirement, but also a reduction in the number of hours worked (from full-time to less than full-time) preserves the general or physical health in the United States. As in the literature analysing the effect of retirement on health outcomes, the main methodological difficulty in these studies is the identification of the effect of working part-time on health outcomes, due to potential endogeneity: changes in health status may induce employees to work part-time, rather than working full-time or retiring. Vaus et al. (2007) and Forbes et al. (2015) do not address the endogeneity of the part-time work decision. The latter two studies have taken different approaches to tackle the potential endogeneity problem. Dave et al. (2008) select individuals who had no major illnesses or health problems in the survey years prior to (partial) retirement and did not report worsening of health between adjacent survey years prior to (partial) retirement. This identification strategy does not exclude the possibility that individuals make use of health care services prior to (partial) retirement or in (partial) retirement. Furthermore, the study excludes individuals who work part-time, and therefore the estimated effects are prone to selection bias. Neuman (2008) uses retirement eligibility ages as instruments for the number of hours worked. This is similar to the approach we adopt in this study. The main difference is that we consider part-time work: Neuman sees those who work less than 1200 hours per year (or three days a week for 50 weeks a year) as retired, implicitly assuming that partial retirement and full retirement are equivalent.

As a second contribution, we add to the new studies which analyze the channels labor market participation affects health outcomes. For example, Insler (2014) analyze behavioral data, such as smoking and exercise, to investigate whether retirement affects health through such channels in the United States. Eibich (2015) find that relief from work-related stress and strain, increased sleep duration, and more frequent physical exercise are potential mechanisms through which retirement affects health in Germany. For the BMI in particular, Abramowitz (2016) analyzes the mechanisms for the association between time spent working and obesity among those between 25 and 64 years old using the American Time Use Survey.

We use the Health and Retirement Study (HRS) to study whether older workers who work part-time or full-time have lower body weight than those who are fully retired. We take an instrumental variable approach to (separately) identify the effects of working part-time and full-time. We use the retirement eligibility ages of the respondent and the partner, job characteristics, and gender as instruments. Employing panel data, we allow for fixed effects, to eliminate the time-invariant factors that are potentially correlated with the number of hours worked. We show that allowing for random effects lead to similar quantitative results. We use the American Time Use Survey to explore the channels working part-time and full-time affect body weight in old age.

We find that working part-time or full-time, instead of retirement, reduces body weight. The effects are sizeable in magnitude. Body weight responds to working part-time much more than it responds to working full-time. This suggests that the effect of the number of hours worked on body weight in old age is not linear. The effects are observed among women. Analysis of time use data shows that while working part-time, women spend substantially less time on two activities that demand the least amount of metabolic energy when compared to all other activities: watching television and sleeping.

This paper proceeds as follows. Section 2 discusses the empirical model. Section 3 describes the data on the BMI and work status indicators. Section 5 presents the results and robustness checks. Section 6 analyzes the channels through which working affects body weight. Section 7 concludes.

2 Empirical approach

2.1 Controlling for heterogeneity

Our aim is to determine the effects of working part-time and full-time on body weight. The first attempt could be to estimate the parameter of interest by ordinary least squares in the following equation:

$$Y_{it} = \alpha + \boldsymbol{D_{it}\beta} + f(A_{it}) + u_{it}. \tag{2.1}$$

Y_{it} is the BMI. $\boldsymbol{D_{it}}$ is a vector of two dummy variables which indicate part-time and full-time work status. In particular, it includes D_{it}^{j} which indicates part-time work if $j = p$, and full-time work if $j = f$. The base work status is retirement. The parameter of interest is the vector $\boldsymbol{\beta}$, which measures the responses of body weight to working part-time and full-time compared to retirement. A_{it} is the age of the individual. $f(A_{it})$ is a flexible and continuous polynomial in age that controls for changes in the BMI with age.

OLS on Equation (2.1) leads to a consistent estimator for $\boldsymbol{\beta}$ only if $\boldsymbol{D_{it}}$ is not correlated with the error term u_{it}. One reason why this assumption may not be satisfied is that individuals might differ from each other because of time-invariant idiosyncratic characteristics that are correlated with the health outcome as well as the retirement behavior. We follow a fixed effects approach to allow for this, augmenting Equation (2.1) as follows:

$$Y_{it} = \alpha + \boldsymbol{D_{it}\beta} + f(A_{it}) + \mu_i + \nu_{it}. \tag{2.2}$$

μ_i is a time-invariant individual specific unobserved variable and it is potentially correlated with $\boldsymbol{D_{it}}$ (and with A_{it}). The remaining error term ν_{it} is assumed to be uncorrelated with the control variables. The main parameters of interest, the effects of working part-time or full-time on the

BMI, are contained in the vector $\boldsymbol{\beta}$. Note that we assume throughout that these 'treatment effects' are assumed to be homogeneous across the population. We will relax this assumption somewhat by estimating the model for specific demographic groups: gender, education level, income level, and self-employment status. Moreover, Murtazashvilia and Wooldridge (2008) have shown that under some additional assumptions the fixed effects instrumental variables estimator that we use remains consistent for the average treatment effect in the model with heterogeneous treatment effects. Following the main studies on this topic referred to above, however, we will not consider models with heterogeneous treatment effects.

Exploiting the panel structure of the data, μ_i is eliminated through the within group transformation:

$$\widetilde{Y}_{it} = \widetilde{\boldsymbol{D}}_{it}\boldsymbol{\beta} + \widetilde{f}(A_{it}) + \widetilde{\nu}_{it}, \tag{2.3}$$

where $\widetilde{Y}_{it}$ represents $Y_{it} - \overline{Y}_i$, etc. The assumption that ν_{it} is uncorrelated with the control variables (strict exogeneity) implies that OLS on Equation (2.2) (the standard within group estimator for static linear panel data models with fixed effects) gives consistent estimates of $\boldsymbol{\beta}$.

2.2 Controlling for endogeneity

A potential problem in Equation (2.3) is that $\widetilde{\boldsymbol{D}}_{it}$ may be correlated with the unobserved $\widetilde{\nu}_{it}$, making the fixed effects estimator for $\boldsymbol{\beta}$ inconsistent. This might happen because, for example, employees carrying more body weight may opt for part-time work or full-time retirement (reverse causation). For example, examining the causal effect of obesity on labor market outcomes, Greve (2008) find that BMI has a negative effect on the employment of women in Denmark. Kinge (2016) find that BMI and obesity significantly increase the probability of not working due to disability.

We follow an instrumental variables approach to address the problem of potential endogeneity of hours worked, exploiting the discontinuities in the probabilities to work part-time and full-time as a function of age at the pension eligibility ages, similar to Coe and Zamarro (2011). The instrumental variables estimation consists of two stages. In the first-stage, we estimate two equations explaining the dummies D^j_{it} for part-time and full-time work:

$$D^j_{it} = \boldsymbol{I}\boldsymbol{\gamma}^j + f(A_{it}) + \eta^j_i + \epsilon^j_{it}. \tag{2.4}$$

$\boldsymbol{I}$ is a vector of indicator variables. It includes indicators of whether the individual is at least as old as a given pension eligibility age, self-employed, able to reduce work hours in current job, and gender. $\boldsymbol{\gamma}^j$ measures the changes in the probabilities of working part-time or full-time due to being eligible for pension benefits, having a certain job characteristic, or being female. Since D^j_{it} is a binary indicator, Equation (2.4) is a linear probability model. The fixed effects η^j_i are time-invariant, individual-specific unobserved variables, and they are potentially correlated with age. Exploiting the panel structure of the data, η^j_i are eliminated through the within group transformation:

$$\widetilde{D}^j_{it} = \widetilde{\boldsymbol{I}}\boldsymbol{\gamma}^j + \widetilde{f}(A_{it}) + \widetilde{\epsilon}^j_{it}. \tag{2.5}$$

The predicted values from the first-stage are used to estimate the main Equation (2.3) in the second-stage:

$$\widetilde{Y}_{it} = \widehat{\widetilde{\boldsymbol{D}}}_{it}\boldsymbol{\beta} + \widetilde{f}(A_{it}) + \widetilde{\upsilon}_{it}. \tag{2.6}$$

$\widehat{\widetilde{\boldsymbol{D}}}_{it}$ represents the within group transformed part-time and full-time work probabilities predicted from Equation (2.5).

The instruments we use are valid only if they are relevant predictors of the part-time and full-time work decisions, and exogenous to the respondent's BMI. In addition, since the model includes two endogenous variables, to separately identify their causal effects, the instruments should offer independent sources of exogenous variation for each endogenous regressor. Otherwise the endogenous variables will be weakly identified (Angrist and Pischke, 2009, pp. 217-218).

It is well documented that the pension eligibility ages are strong predictors of the retirement decision, and we will also check that this is the case for working part-time and full-time in our sample. It also seems quite plausible to assume that BMI does not change discontinuously at the institutionally determined pension eligibility ages. Furthermore, using formal hypothesis tests, we will show that the job characteristics we use and gender are strong predictors of the part-time or full-time work decisions, and that they provide exogenous sources of variation for the part-time and full-time work decisions. Moreover, we will argue that the effects of the instruments on the part-time and full-time work probabilities are heterogenous, and we will also conduct formal hypothesis tests to verify that neither of the two endogenous regressors is weakly identified. If the selected instruments are indeed valid, the causal effect of working part-time or full-time on BMI, measured by $\boldsymbol{\beta}$, is consistently estimated using least squares on Equation (2.6). The complete two-stage estimation procedure corresponds to the two-stage least squares estimation.

3 Data

To analyze the causal of working on the BMI we use the Health and Retirement Study (HRS). HRS is a nationally representative panel study, and surveys more than 22,000 Americans over the age of 50 every two years, along with their spouses or partners. The survey was launched in 1992 and collects information on, among other things, income, work, pension plans, physical health, cognitive functioning, and health care expenditures. We use 12 waves of the survey covering the period from 1992 to 2014.

We impose restrictions on the observations of panel units, or on the panel units (all observations of a given panel unit) as follows. First, we drop respondents who reported they never worked, or who said they worked, but with a tenure of less than five years on all jobs, or if this information was missing altogether in any given survey year. Second, we drop respondents who reported their last job ended before the age of 50 in all survey years, or who reported this in given survey years and this information was missing in other survey years, or if this information was missing in all survey years. Third, we drop respondents who reported to be working, unemployed, disabled, or not in the labor force, after reporting retirement in a previous survey year, so that retirement is an absorbing state. Fourth, we drop the observations of respondents if they were unemployed, disabled or not in the labor force in a given survey year. The reason for this restriction will be explained in Section 3.2. Finally, we drop the observations of respondents if they were younger than 50 years old or older than 75 years old in a given survey year. These sample restrictions lead to an unbalanced panel of 84,979 observations for 19,384 individuals (based on the information available on employment status).

To analyze the channels through which working affects the BMI, we use the American Time Use Survey (ATUS). The survey was launched in 2003. ATUS sample households are chosen from the households that completed their eighth (final) interview for the Current Population Survey (CPS). Respondents are 15 years old or older. Respondents are interviewed by telephone about how they spend their time between 4 a.m. on the day before the interview until 4 a.m. on the day of the interview. Respondents state the activities they did, and how long each activity lasted. The survey collects data on demographic characteristics if they are not already available from the preceding CPS interviews. Furthermore, it collects additional data in supplementary modules such as the Eating and Health module, which includes information, among others, on eating, exercise, and the BMI.

In the ATUS data, time use is not equally represented across the days of the week. While weekend days represent 50 percent of the collected information on time use, each week day represents 10 percent of the collected information. Therefore, we weight the observations using the supplied sample weights so that each day of the week is equally represented among the seven days of the week. Furthermore, we weight the observations of a number of demographic groups using the supplied sample weight so that they are representative of the underlying population.

We impose the following sample restrictions. First, we drop respondents who reported to be unemployed or not in the labor force due to disability or some other reason. Second, we drop women who are pregnant since their reported weights are not likely to be reflective of their usual. Third, we consider the respondents who are interviewed in years 2006, 2007, 2008, 2014, and 2015. The reason for this restriction is that the data for Eating and Health module of ATUS is only available in these years. Fourth, we drop the observations of respondents if they were younger than 50 years old or older than 75 years old in a given survey year. These sample restrictions lead to a cross-section of 13,029 individuals (based on the information available on the BMI).

3.1 Measuring body weight

We consider the body mass index (BMI) as the indicator of body weight. We also construct indexes of overweight and obesity based on the BMI. BMI is given by the weight (in kilograms) divided by the square of height of the respondent (in meters). Following the existing literature, overweight is defined as a BMI greater than 25 and less than or equal to 30; obesity is defined as a BMI greater than 30.

3.2 Measuring work intensity

The aim of our analysis is to examine the effects of working part-time and full-time on the BMI in old age. In the HRS, part-time or full-time work can be defined in various ways. Self-perceived work status, earnings, the number of hours worked per week, or the number of weeks worked per year are all possible indicators of work effort (see, e.g., Gustman and Steinmeier, 2000b). We define full-time work as working 35 or more hours per week for 36 or more weeks per year. As is common in US studies, we define part-time work as working less than 35 hours a week, or as working 35 or more hours a week but less than 36 weeks a year. We define full retirement as working 0 hours a week. The number of work hours includes the hours in the main job as well as those in a possible second job. In the robustness analysis, we check whether the baseline results are sensitive to alternative thresholds for the number of hours worked per week.

Figure 1 presents the distributions of the numbers of hours worked per week and weeks worked per year in the main job in all survey years. The figure shows that most of the respondents are working 35 hours or more a week. Among those working less than 35 hours a week, 68.7 percent are working 20 hours or more a week. The vast majority is working 36 or more weeks a year. In particular, among those working any number of hours, 74.1 percent are working 35 hours or more a week for 36 or more weeks a year, while 20.8 percent are working less than 35 hours a week for 36 or more weeks a year. This suggests that the time spent working part-time or full-time during a week is persistent over a year.

We define part-time work as working less than 35 hours a week, or as working more than 35 hours but less than 36 weeks a year. In the HRS, however, this amount of work effort can correspond to two different labor force participation statuses: 'working part-time' as well as 'partly retired'. If the respondent is working less than 35 hours per week (based on the reported hours of work) and does not mention retirement (based on the reported retirement status), he can be classified as 'working part-time'. If The respondent working under 35 hours and mentions retirement, he can be classified as 'partly retired'. In the robustness analysis, we check whether the baseline results are sensitive to these two different definitions of part-time status.

As explained above, we exclude the observations of respondents if they are disabled or out of the labor force at the time of the survey; in these cases, respondents are not working, not searching for a full-time or part-time job, and do not report to be in retirement. We also exclude when respondents are unemployed. These individuals work 0 hours, but they are likely to be more active than those who are retired, since they report to be searching for a full-time or part-time job.

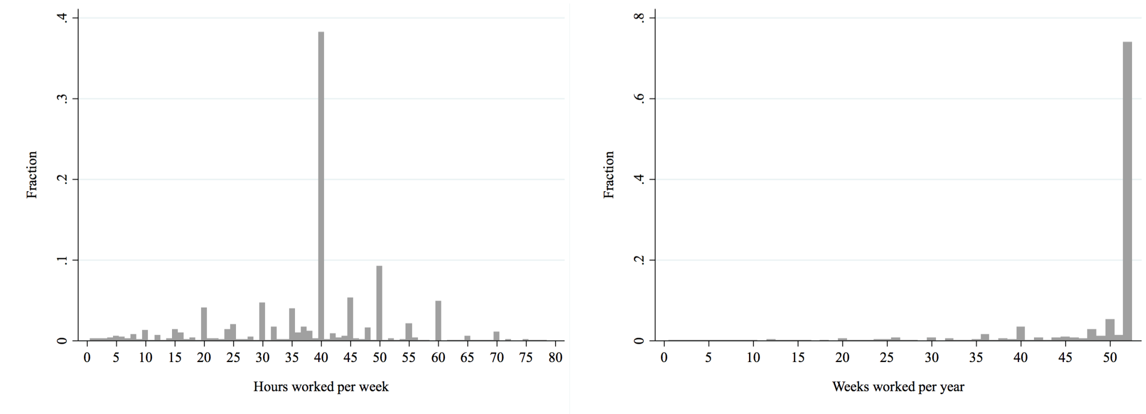

Figure 1: Distributions of hours worked per week and weeks worked per year.

3.3 Instruments

To separately identify the effects of working part-time and full-time, suitable instrumental variables should be found. In particular, the instrument should affect the part-time (full-time) work decision against the retirement decision, while leaving the full-time (part-time) work decision unchanged. We consider a total of nine instruments and analyze whether they provide the particular sources of exogenous variation we need. Three instruments indicate whether respondents are eligible for social security benefits. In particular, the indicators define whether the individual is between the early and normal retirement age, between the normal retirement age but younger than 70, or older than 70. The early and normal retirement ages are presented in Table 1. The literature on the effect of retirement on health shows that retirement ages are significant predictors of retirement behavior and are not likely to explain individual health status directly (Charles, 2004; Rohwedder and Willis, 2010; Coe and Zamarro, 2011; Bonsang et al., 2012; Mazzonna and Peracchi, 2012, 2016). Hence, as predictors of hours of work, dummies for reaching these institutional retirement ages present themselves as natural instruments. We also use an indicator for having reached the age of 70, when the work decisions of individuals might change for two reasons. First, before the year 2000, social security benefits were reduced for those who continued to work at the normal retirement age through age 69 (earnings test). This means that some people might have preferred to return to work or increase their work hours at the age of 70, when they no longer faced the earnings test. Second, individuals are allowed to delay receiving their social security benefits at their normal retirement age until the age of 70 and get compensated for this in the form of increased benefits (in an approximately actuarially fair way). This may induce some people to delay their retirement until they reach the age of 70.

Following Neuman (2008), we also consider three other instruments which consists of the same three age indicators, but then for the married or unmarried partner. Whether the partner is eligible for social security benefits may explain the retirement behavior of an individual, whereas it has no direct effect on the health status of that individual. Indeed, Gustman and Steinmeier (2000a) argue that an individual values retirement more once their spouse has retired. Blau (1998) and Gustman and Steinmeier (2000a, 2004, 2014) provide empirical evidence that couples coordinate their retirement timing. We discuss the robustness of our results to the choice of the instruments in Section 5.4.

Table 1 shows that people born in 1937 or earlier are subject to the normal retirement age of 65, while younger cohorts are subject to a cohort-specific normal retirement age that is scheduled to gradually increase to 67 by year 2027. In our sample, only 6.2 percent of the respondents have faced a cohort-specific normal retirement age during the sample period. 10.2 percent have faced the normal retirement age of 65, while other respondents are still to face a cohort-specific normal retirement age. This means that we lack a convincing source of variation in the normal retirement age across birth cohorts that helps to identify the effects of part-time and full-time work. However, our identification strategy relies on six different eligibility ages for social security benefits, and much less on the variation in the normal retirement age (see Section 2.2).

It is clear that many individuals will opt out of full-time work when they are eligible for social security benefits. This means that early and normal retirement ages are relevant instruments for the dummy variable defining full-time work in our model. Eligibility for social security benefits can also affect the part-time work decisions. Aaronson and French (2004) argue that the financial incentives built in the social security system are likely to induce workers to reduce work hours at the early and normal retirement ages in the United States, and they use the retirement eligibility ages as instruments for working part-time in their analysis of the causal effect of working part-time on wages.

As discussed in Section 2.2, to separately identify the causal effects of part-time and full-time work, it is not sufficient that the retirement ages have explanatory power for the part-time and full-time work decisions, but they should affect these decisions independently. Different retirement ages can affect the full-time work decision in different ways. Individuals will more often stop working full-time at the normal retirement age than at the early retirement age because benefits are substantially reduced if claimed before the normal retirement age. Different retirement ages can also affect the part-time work decision in different ways. Social security regulations allow individuals who have reached their normal retirement age to draw social security benefits and earn work income at the same time. This means that, as of their normal retirement age, individuals may prefer to work part-time rather than retire fully, to supplement their social security benefits with work income, especially if social security benefits constitute their only retirement income. Other individuals who are already working part-time will be less inclined to continue working part-time when they are eligible for early or normal retirement benefits if by then the utility of retirement exceeds the utility of consumption from earned income.

The retirement ages of the partner can affect the work preferences in even more complex ways. Gustman and Steinmeier (2014) describe the different ways the partial or full retirement status of one spouse can affect the part-time and full-time work preferences of the other spouse, and how the retirement status of the wife can have a larger effect on the work preferences of the husband than vice versa. They use their estimated model to simulate the effect of eliminating the labor force participation of the wife on the retirement status of the husband. They consider two offsetting effects. The loss of income from the wife's work could lead the husband to retire later, while the fact that the wife is out of the labor force could increase the value of leisure for the husband and induce him to retire earlier. They find that if the wife is not working, the husband becomes more likely to work part-time or full-time at the early retirement age and beyond, but the probability of working part-time at the normal retirement age is higher than that at the early retirement age, while the opposite is true for working full-time.

Apart from the retirement eligibility ages, we consider three other instruments. First, the HRS asks whether the respondent works for someone else or whether they are self-employed in their current main job. Self-employment status could be used as an instrument for part-time work, but there are no observations available for those who are retired. As an alternative, we define a dummy variable that takes a value of 1 for the panel respondent if the respondent is observed to state he is self-employed in any given wave or in all waves (where data is available) of the survey. According to this definition, we do not exclude from the analysis the respondents who are observed as working (and hence are asked the question) in a given wave, and as retired (and hence have a missing entry for the question) in a subsequent wave. However, we exclude the respondents who are observed as retired in all waves since then there is no available information for these respondents. We expect this variable to be a strong predictor of the part-time work status. In fact, the literature on partial retirement shows that self-employed individuals have better opportunities to work part-time because they face fewer market restrictions and have more flexibility in determining their own working hours (Ekerdt et al., 1996; Kim and DeVaney, 2005). There is also no immediate reason to expect body weight to be different among the self-employed and those who work for an employer.

The HRS asks whether the respondent could reduce paid hours in the regular work schedule. Following the same strategy as for the self-employment status, we define a dummy variable that takes a value of 1 for the panel respondent if the respondent is observed to state he is able to reduce paid hours in any given wave or in all waves. Again, this variable excludes the respondents who are observed as retired in all waves since there is no available information for these respondents. Being able to reduce the number of hours worked seems an obvious indicator of part-time work. However, those who carry more body weight could prefer to work in less demanding part-time jobs. Therefore, we will check whether the instrument offers an exogenous source of variation for working part-time using the test of overidentifying exclusion restrictions.

Finally, we use gender as an instrument for part-time work. Part-time work is likely to be more attractive for the types of work typically done by women and therefore gender presents itself as a relevant predictor of part-time work. However, gender could affect the BMI through channels other than working (Bruce et al., 2007). Again, using the test of overidentifying exclusion restrictions, we will check whether gender offers an exogenous source of variation for the part-time work decision.

The use of the three instruments defined above is restricted in two respects. First, the observations of each instrument do not vary over time for a given panel respondent. This means that the fixed effects model we use cannot accommodate these instruments. Therefore, we will estimate a random effects model to use these instruments. Second, the question on whether the respondent is able to reduce paid hours is asked if the respondent states that he is doing paid work and hence is not self-employed. This means that we cannot consider a linear combination of the two instruments which inform on whether the respondent is able to reduce paid hours and whether the respondent is self-employed. Instead, we will use these instruments in combination with the other instruments and check whether using them leads to more precise estimates of the effects of working part-time or full-time.

Table 2 presents the fraction of individuals in four employment states, based on reported hours of work and retirement status, before the age at which they become eligible for social security, between the early and normal retirement ages, and after the normal retirement age. The table also presents the fractions by the retirement eligibility ages of the partner. In the table we distinguish between two modes of part-time status: part-time workers and part-time retirees. It appears that the retirement eligibility ages of both the respondent and those of the partner change the fraction of those who work full-time and part-time, and accordingly the fractions of those who are retired. The changes are larger at the retirement ages of the respondent than at those of the partner. Furthermore, the eligibility ages differ from each other in how much they change these fractions. The changes in the fraction of those who work full-time appear to be more substantial than the changes in the fraction of those who work part-time. This might suggest that the retirement eligibility ages offer a particular source of exogenous variation for working full-time alone. In Section 5, using a formal hypothesis test, we will check whether the retirement eligibility ages indeed offer independent sources of exogenous variation for working part-time and full-time making them suitable instruments to separately identify the effects of them.

The lower panel of Table 2 presents the fraction of individuals in four employment states with respect to the dummy variable categories of the three instruments on job characteristics and gender. Across the two categories of the dummy variable on self-employment, it appears that while the fraction of those who work full-time changes only marginally, the fractions of those who work part-time and who are retired change considerably. We observe a similar pattern across the two categories of the dummy variable indicating whether the respondent is able to reduce paid hours. The reasons behind observed work choices of these subpopulations seem obvious: they are less likely to face institutional restrictions to reduce hours and be forced to retire at the retirement ages and are therefore able to trade off retirement with working part-time. These figures suggest that both job characteristics would perform particularly well as instruments: they change the preferences to work part-time while leave the preferences to work full-time unchanged. Considering gender, women are more often working part-time or retired, and they are less often working full-time. The difference in the fractions of those working full-time across the two gender groups is larger than that of those who are retired, suggesting that gender is predictive of the part-time work decision against the full-time work decision rather than against the retirement decision.

Table 1: Retirement eligibility ages

Year of birth	Retirement eligibility ages		
	Early	Normal	Late
1937 or earlier	62	65	70
1938	62	65 and 2 months	70
1939	62	65 and 4 months	70
1940	62	65 and 6 months	70
1941	62	65 and 8 months	70
1942	62	65 and 10 months	70
1943-1954	62	66	70
1955	62	66 and 2 months	70
1956	62	66 and 4 months	70
1957	62	66 and 6 months	70
1958	62	66 and 8 months	70
1959	62	66 and 10 months	70
1960	62	67	70

Source: The United States Social Security Administration.

Table 2: Employment rates by the categories of the dummy variables as instruments (%)

	Full-time worker	Part-time worker	Part-time retiree	Full-time retiree
Retirement ages of the respondent				
Under early ret. age	72.76	11.83	4.34	11.06
Between early and normal ret. age	37.67	6.63	11.98	43.71
Between normal ret. age and age 70	18.20	4.48	12.90	64.41
Over age 70	7.82	4.04	9.62	78.51
Retirement ages of the partner				
Under early ret. age	66.99	9.98	6.03	16.99
Between early and normal ret. age	38.53	8.22	10.40	42.85
Between normal ret. age and age 70	24.31	6.31	11.52	57.85
Over age 70	13.13	5.67	9.52	71.67
Observed self-employed when working				
Always or ever observed self-employed	52.10	14.26	16.95	16.68
Always observed doing paid-work	55.41	8.36	6.48	29.75
Observed able to reduce paid hours when working				
Always or ever observed able to reduce paid hours	56.48	11.63	12.14	19.75
Always observed not able to reduce paid hours	58.33	5.79	3.35	32.53
Gender				
Men	58.56	5.30	9.69	26.45
Women	43.61	12.56	7.26	36.57

Notes: 1. Other employment status groups ‘disabled’, ‘not in the labor force’, and ‘unemployed’ are excluded from the analysis. 2. Totals may not add due to rounding error.

3.4 Descriptive statistics

Table 3 presents descriptive statistics for the full sample selected using the exclusion criteria in Section 3. It also presents the statistics for the first and last wave of the survey so that changes in the statistics can be compared over time. Over the whole survey period, the average age of the sample is 62.2 years, where 14.1 percent are between the early and normal retirement ages, and 34.3 percent are at or above the normal retirement age. 48.4 percent have some college or a higher degree. 75.3 percent of the sample are married or have a partner.

40.9 percent of the sample are overweight, and 28.2 percent are obese. 37.7 percent of the sample are overweight and 37.1 percent are obese in 2012. These figures are in line with those presented by Flegal et al. (2010).

47.3 percent of the sample report working 35 hours or more per week, while 16.3 percent report working less than 35 hours at the time of the survey. The sample consists mainly of white-collar workers. There are plausible changes in the statistics between the first and last waves. The most notable change is that health status deteriorates across all health indicators except for overweight and word recall.

Table 3: Descriptive statistics (%)

	All waves	1992 wave	2012 wave
Age (50–75) (avg.)	62.23	57.11	62.21
Under early ret. age	51.68	87.34	52.75
Between early and normal ret. age	14.06	6.73	17.20
Between normal ret. age and age 70	16.35	4.60	11.40
Over age 70	17.91	1.33	18.65
High education	48.45	40.78	56.91
Spouse or unmarried partner	75.28	80.90	71.39
Female	47.67	39.26	52.93
Overweight	40.87	43.03	37.71
Obese	28.25	20.49	37.12
Part-time worker	16.26	15.55	16.11
Full-time worker	47.27	68.97	47.30
Retired	36.45	15.47	36.59
White-collar (former) worker	60.32	57.06	60.10
Self-employed	20.22	18.55	18.97
N obs.	84979	6256	8913
N ind.	19384		

Notes: 1. Number of observations is based on the information available on employment status. 2. Totals may not add due to rounding error.

4 Exploratory graphical analysis

Our aim is to investigate whether body weight depends on working part-time and full-time in old age. In our empirical approach, we use, among other instruments, the retirement eligibility ages of the respondent and his or her partner as determinants of part-time and full-time work decisions. Here we first provide exploratory graphical analysis of the differences in the conditional mean of the BMI among part-time workers, full-time workers, and retirees aged between 50 and 75. With respect to our identification strategy, we then provide graphical analysis of the jumps in the conditional mean of the part-time and full-time work status at the retirement eligibility ages.

Figure 2 presents univariate nonparametric regression of body weight against the age of the individual by work status, distinguishing among full-time workers, part-time workers, and retirees. We also draw 95 percent confidence bounds around each curve. The notable patterns are the following. First, the bounds of the curves of the three work status groups do not cross until about age 65, suggesting that the differences among these groups are statistically significant until this age. Second, both part-time and full-time workers have a lower mean BMI across all ages, but this is most pronounced for part-time workers. This suggests that body weight and number of hours worked in old age do not have a linear relationship. Third, all work status groups share a common trend of decreasing BMI with age, but the rate of the decrease differs across these groups. A potential explanation for the downward trend in the BMI is the loss of muscle tissue due to ageing (Kyle et al., 2001). The heterogeneity in the rate of muscle tissue loss across the work status groups seems to confirm this explanation: the rate of decrease is higher for retired individuals perhaps because they engage in physically demanding activities less often.

Figure 3 presents univariate nonparametric regressions of the probabilities of working full-time, working part-time, and part-time retirement against the age of the individual and against the age of his or her partner, allowing for jumps at the retirement eligibility ages. There are obvious discontinuities at the cutoff ages, and the jumps are in the expected direction. The bounds often do not cross the curves, suggesting that these jumps are statistically significant. The jumps are more pronounced at the cutoff ages of the individual than at those of their partner, however. The jumps show that full-time work and part-time work or part-time retirement probabilities change significantly at the retirement eligibility ages, which supports our identification strategy. However, note that the plot is based on univariate regression and does not control for the effect of the partner's age. In the next section, we present formal tests of whether the dummy variables for the discontinuities are jointly powerful enough to serve as good instruments for both part-time and full-time work status.

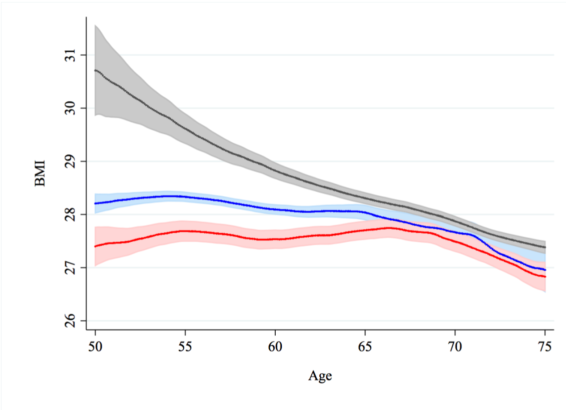

Figure 2: BMI by age of the respondent among retirees (grey), full-time workers (blue) and part-time workers (red). Kernel smoothed local polynomials and 95 percent confidence intervals around them.

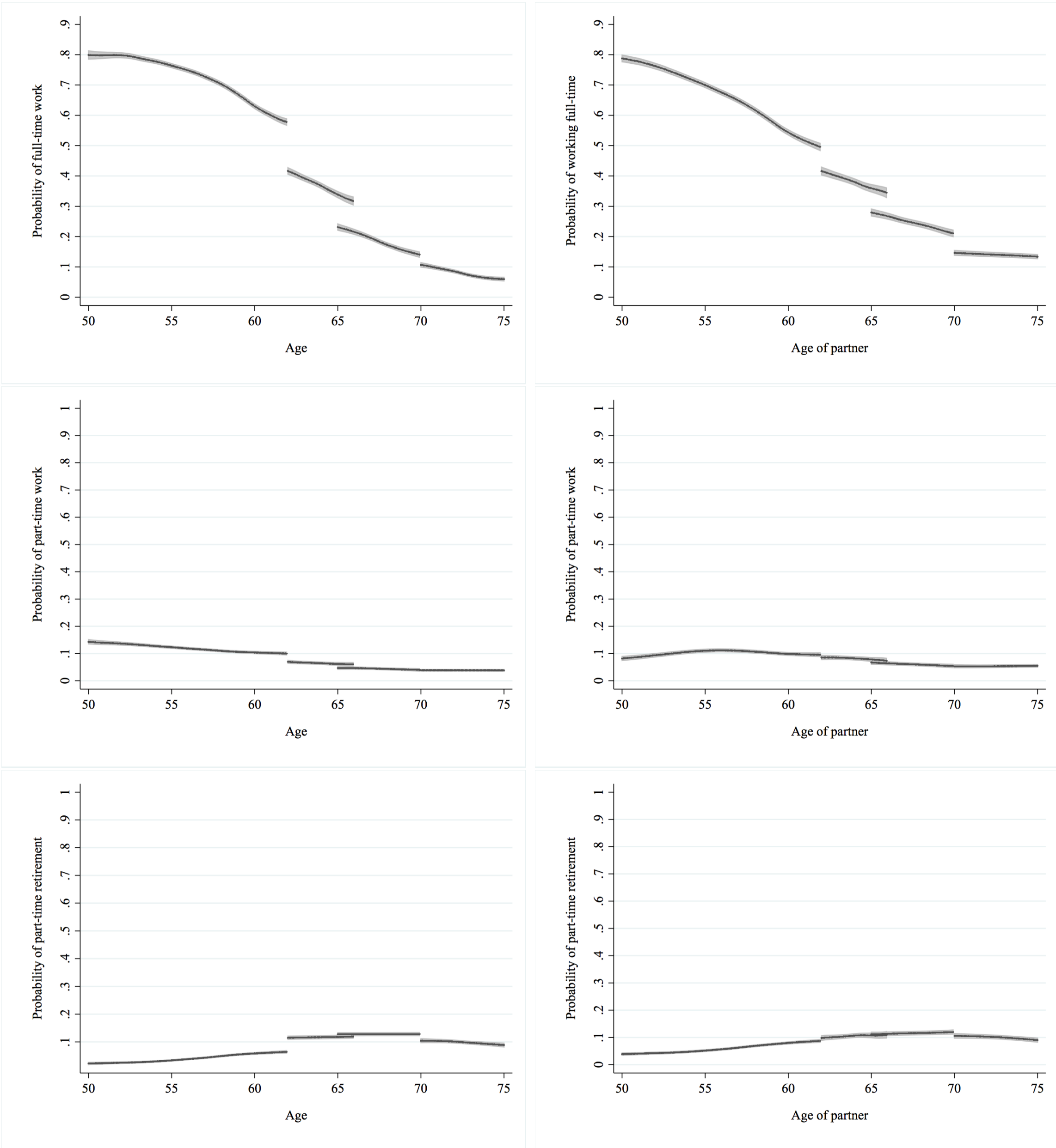

Figure 3: Probabilities of full-time work, part-time work, and part-time retirement by age of the respondent allowing for jumps at the retirement eligibility ages. Kernel smoothed local polynomials and 95 percent confidence intervals around them.

5 Results

5.1 Instrument relevance and validity

Table 4 presents the coefficient estimates from the first-stage estimation of the linear probability model with fixed effects given by Equation (2.5). The errors of the linear probability model are heteroskedastic by construction of the model, and the predictions of the model may lie outside the unit interval. We correct the standard errors of the estimates for heteroskedasticity. In 239 cases the predictions of the model lie outside the unit interval for the full-time work regression. Dropping these cases does not change our qualitative results. Furthermore, this does not affect the consistency of the fixed effects instrumental variables estimator that we use.

Table 4 shows that the retirement eligibility ages of the respondent significantly change the probabilities of both working part-time and full-time. The changes are particularly large for working full-time, however. This is plausible since the majority of the employees opt out of full-time work when they are eligible for social security benefits according to Table 2. The retirement ages of the partner are also predictive the respondent's own work decisions but especially of the part-time work decision. These results suggest that one's own retirement ages and the retirement ages of his or her partner provide fairly independent sources of exogenous variation for working part-time and full-time, respectively. We will provide further evidence for this claim in our robustness checks. Furthermore, the sizes of the effects of the retirement ages also appear to be fairly heterogenous. The effects of one's own retirement ages are usually larger than the effects of the partner's retirement ages. This is in line with the observed jumps in the probabilities of working full-time and part-time in Figure 3 that are more pronounced at the retirement ages of the individual than at those of the partner. The retirement age indicators are jointly significant at the 0.01 level in both regressions of part-time and full-time work.

Angrist and Pischke (2009, pp. 217-218) introduced the first-stage conditional F statistic which tests whether an endogenous regressor alone is weakly identified in models with multiple endogenous variables. The statistic is later improved by Sanderson and Windmeijer (2016). The statistic is based on a two-step regression procedure. First, an endogenous regressor is regressed on the first-stage fitted values of the remaining endogenous regressor and other exogenous regressors. The residuals from this regression are then regressed on the instruments. Joint significance of the instruments provides evidence against weak identification for the particular endogenous regressor. Table 4 presents the Sanderson and Windmeijer conditional F statistic for each endogenous regressor. The results suggest that the instruments are not weak for any of the two endogenous regressors and hence separately identify the causal effects of the endogenous regressors. Cragg and Donald (1993) introduced the second-stage F statistic to test for weak identification. Stock and Yogo (2005) tabulated critical values for the test for two particular consequences of weak instruments: bias of the instrumental variable estimator relative to the bias of the least squares estimator, and distortion of the test size. However, the test, and the critical values tabulated for the test, are valid under the assumption that the regression errors are independently and identically distributed. The value of the test is 18.259 and exceeds the critical value of 15.72 for 5 percent maximum relative bias, and it lies between the critical values of 12.33 and 21.68 for 15 and 10 percent maximum test size distortions, respectively. In line with the Sanderson-Windmeijer test, the Cragg-Donald test provide no particular evidence to suspect that our model is affected by a weak instruments problem. On the contrary, these tests provide strong statical evidence that the instrumental variables we use offer independent sources of exogenous variation to separately identify the effects of working part-time and full-time.

Table 5 presents the results of the overidentifying restrictions test when we consider the retirement eligibility ages of both the respondent and the partner, which constitute a total of six instrumental variables for two potentially endogenous regressors. Table 8 presents the results when we consider the retirement eligibility ages of the respondent alone (three instruments for two regressors), and when we consider the retirement eligibility ages of the partner alone. All the test results support the use of these instruments: the null hypothesis that all moment restrictions are valid is not rejected.

Table 4: Results for first-stage FE model explaining part-time and full-time work status

	Part-time		Full-time	
	Coef.	S. E.	Coef.	S. E.
Bet. early and normal ret. age	0.036***	0.005	−0.162***	0.006
Bet. normal ret. age and age 70	0.045***	0.008	−0.242***	0.009
Over age 70	0.031***	0.011	−0.207***	0.012
Bet. early and nor. ret. age (P)	−0.011	0.005	−0.027***	0.006
Bet. nor. ret. age and age 70 (P)	−0.040***	0.008	−0.021**	0.009
Over age 70 (P)	−0.084***	0.012	0.012	0.013
Age	0.016**	0.006	0.001	0.006
Age squared	−0.000**	0.000	−0.000***	0.000
Constant	−0.348*	0.189	1.359***	0.202
F test for quadratic age	5.500***		542.810***	
F test for excluded instruments	18.730***		178.270***	
Weak identification test	12.808***		37.573***	
N. obs.	68129			
N. ind.	14553			

Notes: 1. Linear probability model with fixed effects. 2. P: Married or unmarried partner. 3. ***, **, * indicate statistical significance at the 0.01, 0.05, 0.10 levels, respectively. 4. Weak identification test tests the null hypothesis that the particular endogenous regressor alone is not identified. The test is based on the Sanderson-Windmeijer F statistic. 5. Standard errors and test statistics are robust to heteroskedasticity and clustering on panel groups.

5.2 Body weight

Table 5 presents the baseline results from the estimation of the linear model with instrumental variables and fixed effects given by Equation (2.6). The estimation makes use of the full set of six instruments introduced above. A first main observation is the following. We find a significant effect BMI. This result reflects the BMI pattern observed in Figure 2. That is, the curves based on univariate nonparametric regressions of the three work status groups do not cross, although their confidence bounds cross after about the normal retirement age.

Regarding the labor market participation at the extensive margin, we find that working (either part-time or full-time) substantially reduces the BMI, implying that older people who work are much less likely to be overweight or obese than those who are retired. Chung et al. (2009) use the same survey data we use, and also find that retirement leads to a higher BMI. However, the marginal effect of retirement they obtain is less significant and substantially smaller (significant at the 5 percent level, with a magnitude of 0.242) than the marginal effects of both working part-time and full-time we obtain. The finding is also in line with Godard (2016) who shows that retirement increases the probability of being obese among men in Europe. This finding may imply that people who remain in the labor market are less prone to diseases caused by overweight. In fact, Liu et al. (2009) find that people who continue to work after retirement have fewer chronic diseases like heart problems or functional limitations than people who are fully retired in the United States. We explore the channels through which labor market participation affects body weight in Section 6.

Regarding labor market participation at the intensive margin, surprisingly, we find that the effect of working part-time is much larger than the effect of working full-time, and we reject the equality of the coefficients of working part-time and full-time at the 0.05 level (as indicated in the table with a double dagger symbol (‡)). The reason for this result can be that part-time workers are not only challenged with activities at work, as full-time workers are, but also with activities outside work, and are therefore more inclined to respond to body weight. It can also be that while working part-time, individuals substitute the additional free time from work with time spent on physical exercise or other physically demanding tasks such as household activities. Again, we explore the channels through which working affects body weight in Section 6.

The result on the BMI is consistent with Au and Hollingsworth (2011), who studied 5164 participants in the Australian Longitudinal Study on Women's Health in 2003 and 2006 to investigate the influence of employment patterns on weight gain and weight loss in young adult women. They found that women in part-time work have a higher probability of losing weight or a lower probability of gaining weight compared to women in full-time work. The authors argue that more time spent at work contributes to weight gain through reduced time available for physical activity, overeating due to work related stress, reduced sleep, or increased preference for fast-food instead of home-cooked meals. These results also suggest that labor market participation affects body weight, as implied by the strand of the literature analyzing the effect of retirement on various health outcomes, but the effect of participation is not independent of the number of hours worked.

Table 5 shows that the age terms are jointly significant at the 0.05 level. This suggests that the quadratic function of age captures well the evolution of body weight through older ages observed in Figure 2. Many of the subject studies also employ a quadratic function or even a linear function of age (Coe and Zamarro, 2011; Dave et al., 2008). We discuss additional results based on linear and cubic age functions in our robustness checks.

5.3 Heterogenous treatment effects

A potential shortcoming of our model is that it is not flexible enough to capture differences in the treatment effects across people with different socio-economic characteristics. To see if such differences play a role, we carry out separate regressions for the groups of the following socio-economic characteristics: gender, education level, income level, and self-employment status. We present the results in Table 7.

Compared to the findings using the full sample, for men, the effects become insignificant, and we fail the test of the endogeneity of hours worked. The effects remain significant and their sizes become larger for women. The effect of part-time work is somewhat less significant, but this is either because the predictive power of the instruments on part-time work is somewhat weaker for women in the first-stage regression, or because the number of observations used in the estimation is about half of that in the full sample. In Figure 4, we present univariate nonparametric regressions of the BMI against the age of the individual where we distinguish by work status, as in Figure 2, but also by gender. The figure helps to explain the results we obtain. The curves are clearly distinct from each other for women while this is not true for men, confirming the significant effects we obtain for women but not for men in Table 7. In fact, our analysis of the channels number of hours worked affects body weight in Section 6 will confirm the gender effect we find here.

We obtain similar results for low income earners and for those with low education as for women. These results suggest that low income earners and low educated lead life styles or adapt eating habits that make them more prone gaining weight.

Table 5: Results for IV-FE model explaining BMI

	BMI	
	Coef.	S. E.
Part-time	-3.054^{***}‡	1.003
Full-time	-0.855^{***}	0.275
Age	0.558^{***}	0.054
Age squared	-0.004^{***}	0.000
End. test	14.082^{***}	
Ove. test	1.721	
F test for work status	10.760^{***}	
F test for quadratic age	187.200^{***}	
N. obs.	65843	
N. ind.	12998	

Notes: 1. Linear model with instrumental variables and fixed effects. 2. The model employs six instrumental variables consisting of the retirement eligibility age indicators for the respondent and the partner. 3. BMI takes values from 10.9 to 82.7. Higher values indicate increasing body weight. 4. ‡ indicates that equality of the coefficients of part-time and full-time is rejected at the 0.05 level. 5. Endogeneity test (denoted as End. test) tests the null hypothesis that the variables 'part-time' and 'full-time' are exogenous. The test is based on the C statistic. Overidentification test (denoted as Ove. test) tests the null hypothesis that all instruments are uncorrelated with the unobserved error. The test is based on the Hansen J statistic. 7. Standard errors and test statistics are robust to heteroskedasticity and clustering on panel groups. 8. ***, **, * indicate statistical significance at the 0.01, 0.05, 0.10 levels, respectively.

Table 6: Results for IV-FE model explaining health outcomes across socio-economic groups

	BMI							
	Female		Male		Low income		High income	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Part-time	-4.201^{**}	2.019	1.129	1.989	-3.166^{***}‡	1.127	2.124	4.329
Full-time	-1.192^{***}	0.391	-0.260	0.532	-0.841^{***}	0.301	0.470	1.892
End. test	12.739^{***}		0.370		10.735^{***}		0.382	
Ove. test	0.823		5.052		0.544		2.636	

Notes: 1. Linear model with instrumental variables and fixed effects. 2. The model employs six instrumental variables consisting of the retirement eligibility age indicators for the respondent and the partner. 3. BMI takes values from 10.9 to 82.7. Higher values indicate increasing body weight. 4. All regressions include age terms. 5. ‡ indicates that equality of the coefficients of part-time and full-time is rejected at the 0.05 level. 6. Endogeneity test (denoted as End. test) tests the null hypothesis that the variables 'part-time' and 'full-time' are exogenous. The test is based on the C statistic. Overidentification test (denoted as Ove. test) tests the null hypothesis that all instruments are uncorrelated with the unobserved error. The test is based on the Hansen J statistic. 7. Standard errors and test statistics are robust to heteroskedasticity and clustering on panel groups. 8. ***, **, * indicate statistical significance at the 0.01, 0.05, 0.10 levels, respectively.

Table 7: Results for IV-FE model explaining health outcomes across socio-economic groups

	BMI							
	Female		Male		Low education		High education	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Part-time	-4.201^{**}	2.019	1.129	1.989	-3.331^{**}	1.482	-2.789^{**}‡	1.374
Full-time	-1.192^{***}	0.391	-0.260	0.532	-0.991^{***}	0.362	-0.624	0.438
End. test	12.739^{***}		0.370		8.582^{**}		5.812^{*}	
Ove. test	0.823		5.052		1.219		3.394	

Notes: 1. Linear model with instrumental variables and fixed effects. 2. The model employs six instrumental variables consisting of the retirement eligibility age indicators for the respondent and the partner. 3. BMI takes values from 10.9 to 82.7. Higher values indicate increasing body weight. 4. All regressions include age terms. 5. ‡ indicates that equality of the coefficients of part-time and full-time is rejected at the 0.05 level. 6. Endogeneity test (denoted as End. test) tests the null hypothesis that the variables 'part-time' and 'full-time' are exogenous. The test is based on the C statistic. Overidentification test (denoted as Ove. test) tests the null hypothesis that all instruments are uncorrelated with the unobserved error. The test is based on the Hansen J statistic. 7. Standard errors and test statistics are robust to heteroskedasticity and clustering on panel groups. 8. ***, **, * indicate statistical significance at the 0.01, 0.05, 0.10 levels, respectively.

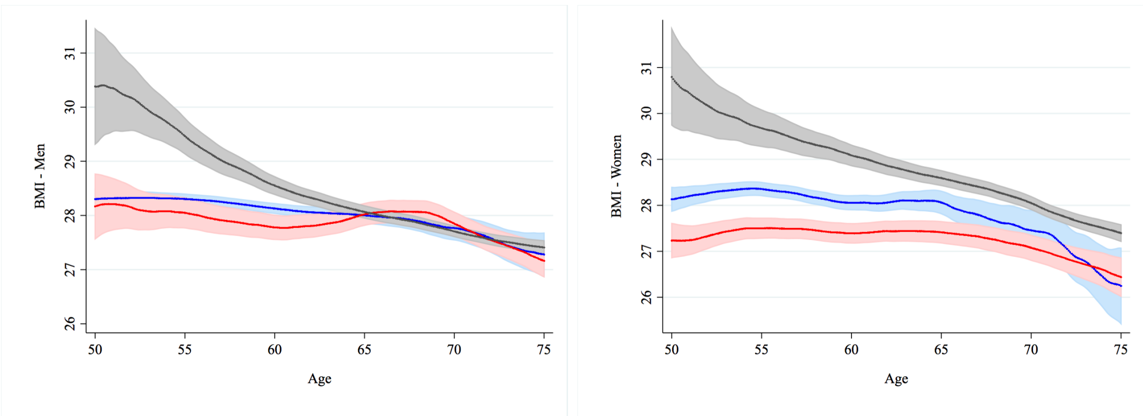

Figure 4: BMI by age of the respondent among full-time workers (blue), part-time workers (red), and retirees (grey) for men (left panel) and women (right panel). Kernel smoothed local polynomials and 95 percent confidence intervals around them.

5.4 Robustness checks

Instrumental variables and identification

In Section 5 we used dummies for reaching institutional retirement ages to identify the causal effects of working full-time and part-time on body weight. Here we carry out a number of robustness checks to find additional support that these effects are identified.

Table 4 showed that one's own retirement ages have larger and more significant effects on the full-time work decision, while those of the partner have larger and more significant effects on the part-time work decision. This suggested that the two types of instruments offer independent sources of exogenous variation for the two types of work decisions. The conditional F statistic confirmed that the six instruments separately identify the effects of working full-time and part-time. Here we estimate two regressions each using a restricted set of instruments. The first set is restricted to the retirement ages of the respondent, and the second set is restricted to the retirement ages of the partner. If the retirement ages of the respondent are providing exogenous sources of variation for the full-time work decision, independently or more than the retirement ages of the partner provide, then the coefficient of full-time work should preserve its statistical significance while the coefficient of working part-time should lose its statistical significance when we restrict the instrument set to the retirement ages of the respondent compared to when we use the full instrument set. Similarly, if the retirement ages of the partner are providing exogenous sources of variation for the part-time work decision, independently or more than the retirement ages of the respondent provide, the coefficient of part-time work should preserve its statistical significance while the coefficient of full-time work should lose its statistical significance when we restrict the instrument set to the retirement ages of the partner compared to when we use the full instrument set. Table 8 presents the results from the estimation of the models each using a restricted set of instruments. The results compare to the results from the estimation of the baseline model using the full instrument set in Table 5, and largely confirm our expectations. These results provide evidence that one's own retirement ages and the partner's retirement ages separately identify the effects of working full-time and part-time.

The coefficient estimates of working full-time and part-time have a Local Average Treatment Effect (LATE) interpretation (Imbens and Angrist, 1994). That is, the estimated effects of working full-time and part-time are specific to subgroups of the population who change their work preferences due to becoming eligible for pension incentives at specific ages. This means that it is not clear if the estimated effects reflect the preferences of other subgroups of the population who change their number of work hours preferences due to reasons other than the pension incentives. Consequently, the estimated effects of working full-time and part-time are not necessarily homogenous across different subgroups of the population. For example, the retirement ages create incentives to retire for subgroups of older workers who face mandatory retirement at these ages, or cannot afford earlier retirement with actuarially penalised pension benefits, among other possible reasons. This means that other subgroups of older workers who do not face such institutional or budgetary constraints should have less incentive to retire at these ages. For this latter group, the retirement ages should have limited explanatory power for the endogenous variables, and lead to less significant effects in the reduced form regression. We distinguish between workers in paid employment and those self-employed who are likely to face different institutional restrictions and different incentives to retire (Parker and Rougier, 2007). We estimate the instrumental variable regression separately for the two subgroups. The first-stage results show that the retirement ages of both the respondent and the partner have much smaller and less significant effects on the probabilities of working full-time and part-time when we use the sample on self-employed workers compared to when we use the sample on workers in paid employment. The second-stage results show that the effects of working full-time and part-time are not significant and we fail the specification tests when we use the sample on self-employed workers, while the effects are significant and the specifications test results are favourable when we use the sample on workers in paid employment. These results suggest that the retirement ages identify the effects of working full-time and part-time for the expected subgroup of the population as the LATE theorem suggests. The results also suggest that the retirement ages act as valid instruments and identify the effects of working full-time and part-time.

We have used dummies for reaching retirement eligibility ages to identify the effects of working full-time and part-time. As discussed above, these instruments might identify the effects of working full-time and part-time for certain subgroups of the population. To address this concern, we employ new instruments instead of the dummies for reaching retirement eligibility ages, or in combination with them.

As introduced in Section 3.3, the instruments are indicators of ever or always observed self-employed, ever or always observed able to reduce paid hours, and male. If these instruments preserve or improve the statistical precision of the estimated effects, we can conclude that the part-time and full-time effects are likely to be homogenous across subpopulations and not specific to certain groups retiring due to pension incentives. In fact, the new instruments represent subpopulations that face different institutional restrictions and different incentives to retire than those who work for an employer or have less discretion over their work schedules.

Table 9 presents the first-stage results using the random effects estimator and the retirement ages of the respondent and his or her partner as instruments. Compared to the first-stage results using the fixed effects estimator and the same set of instruments presented in Table 4, the retirement ages of the partner appear to be strong predictors of working full-time against retirement, rather than working part-time. One's own retirement ages remain as strong predictors of the full-time work decision against the retirement decision. Table 10 presents the first-stage results using the random effects estimator and when we supplement the retirement eligibility ages with a new instrument at a time. There are two main findings. The indicator of self-employment status appears as a strong predictor of working part-time against retirement. This is also true for the indicator of whether the respondent is able to reduce paid hours. On the other hand, the indicator of whether the respondent is male appears to be a strong predictor of both working part-time and full-time. This means that as an instrument this indicator has little power to identify the work status of the respondent against retirement. Therefore, we do not expect this instrument to lead to significant effects for working part-time and full-time in the reduced form models we estimate below.

Table 11 presents the results from the estimation of the reduced form model allowing for random effects and using the baseline instrumental variables (retirement ages of the respondent and his or her partner). These results compare to the reduced form results allowing for fixed effects presented in Table 5. Table 12 presents the results from the estimation of a number of reduced form models which allow for random effects and use the baseline and new instrumental variables. In particular, Model 1A uses the same set of six instruments in our baseline model, and supplements this set with the indicator of self-employment status. Model 1B uses a restricted set of retirement age indicators (indicators of whether the respondent and his or her partner is between the normal retirement age and age 70), and supplements this set with the indicator of self-employment status. Models 2A and 2B, Models 3A and 3B resemble Models 1A and 1B but instead of an indicator of self-employment status, they consider, respectively, indictors of whether the respondent is able to reduce paid hours and whether the respondent is male. The main finding is that, compared to the estimated effects in the model using the baseline instrument set in Table 11, the new instruments on self-employment and ability to reduce paid hours preserve or improve the statistical precision of the coefficient estimates regardless of that we employ the full or a restricted set of retirement eligibility ages as instruments (Models 1A, 1B, 2A, 2B). This suggests that the effects we find for working part-time and full-time in Table 5 are not driven by the specific work preferences of subpopulations that change with pension incentives, but by the work preferences of individuals that can change for any reason including the pension incentives.

A second finding is that the coefficient estimate of working part-time is not significant in Model 3B where we employ two indicators for pension eligibility and the indicator of male. This result is not surprising. As discussed above, the indicator of whether the respondent is male has little power to identify the part-time work decision against retirement. On the other hand, the coefficient estimate of working full-time is still significant since the retirement age indicators are predictive of the full-time work decision against the retirement decision.

Table 8: Robustness check on the instrument set

	BMI			
	Eligibility ages: own		Eligibility ages: partner	
	Coef.	S. E.	Coef.	S. E.
Part-time	-4.118^{*}	2.343	-3.045^{***}‡	1.037
Full-time	-1.100^{**}	0.480	-0.451	0.575
End. test	8.514^{**}		10.692^{***}	
Ove. test	0.394		0.770	
N. obs.	88889		65843	
N. ind.	16978		12998	

Notes: 1. Linear models with instrumental variables and fixed effects. 2. BMI takes values from 10.9 to 82.7. Higher values indicate increasing body weight. 3. ‡ indicates that equality of the coefficients of part-time and full-time is rejected at the 0.05 level. 4. Endogeneity test (denoted as End. test) tests the null hypothesis that the variables 'part-time' and 'full-time' are exogenous. The test is based on the C statistic. Overidentification test (denoted as Ove. test) tests the null hypothesis that all instruments are uncorrelated with the unobserved error. The test is based on the Hansen J statistic. 5. Standard errors and test statistics are robust to heteroskedasticity and clustering on panel groups. 6. ***, **, * indicate statistical significance at the 0.01, 0.05, 0.10 levels, respectively.

Table 9: Results for first-stage RE model explaining part-time and full-time work status

	Part-time		Full-time	
	Coef.	S. E.	Coef.	S. E.
Bet. early and normal ret. age	0.032***	0.005	−0.163***	0.006
Bet. normal ret. age and age 70	0.037***	0.008	−0.240***	0.009
Over age 70	0.020*	0.011	−0.202***	0.012
Bet. early and nor. ret. age (P)	0.008	0.005	−0.049***	0.006
Bet. nor. ret. age and age 70 (P)	−0.009	0.007	−0.060***	0.008
Over age 70 (P)	−0.035***	0.009	−0.054***	0.009
Age	0.012**	0.006	−0.001	0.006
Age squared	−0.000**	0.000	−0.000***	0.000
Constant	−0.177	0.176	1.349***	0.186
F test for quadratic age	4.624*		1177.481***	
F test for test for excluded instruments	87.889***		1238.922***	
Weak identification test	11.643***		20.567***	
N. obs.	68151		68151	
N. ind.	14556		14556	

Notes: 1. Linear probability model with random effects. 2. P: Married or unmarried partner. 3. ***, **, * indicate statistical significance at the 0.01, 0.05, 0.10 levels, respectively. 4. Weak identification test tests the null hypothesis that the particular endogenous regressor alone is not identified. The test is based on the Sanderson-Windmeijer F statistic. 5. Standard errors and test statistics are robust to heteroskedasticity and clustering on panel groups.

Table 10: Results for first-stage RE model explaining part-time and full-time work status

	Extra IV: Observed self-employed				Extra IV: Observed able to reduce hours				Extra IV: Male			
	Part-time		Full-time		Part-time		Full-time		Part-time		Full-time	
	Coef.	S. E.	Coef.	S. E.	Coef.	S. E.	Coef.	S. E.	Coef.	S. E.	Coef.	S. E.
Bet. early and normal ret. age	0.035***	0.006	−0.163***	0.007	0.041***	0.007	−0.170***	0.008	0.033***	0.005	−0.164***	0.006
Bet. normal ret. age and age 70	0.043***	0.010	−0.240***	0.010	0.050***	0.011	−0.249***	0.012	0.040***	0.008	−0.244***	0.009
Over age 70	0.026*	0.015	−0.186***	0.015	0.032*	0.016	−0.191***	0.017	0.024**	0.011	−0.207***	0.012
Bet. early and nor. ret. age (P)	0.007	0.005	−0.062***	0.006	0.007	0.006	−0.059***	0.007	−0.006	0.005	−0.034***	0.006
Bet. nor. ret. age and age 70 (P)	−0.010	0.008	−0.073***	0.009	−0.013	0.008	−0.073***	0.010	−0.030***	0.007	−0.037***	0.008
Over age 70 (P)	−0.032***	0.010	−0.060***	0.011	−0.042***	0.012	−0.057***	0.012	−0.071***	0.009	−0.013	0.010
Observed self-employed	0.165***	0.007	−0.024***	0.008								
Able to reduce hours					0.149***	0.006	−0.023***	0.006				
Male									−0.100***	0.005	0.116***	0.006
Age	0.008	0.008	0.043***	0.008	0.010	0.008	0.061***	0.008	0.011*	0.006	−0.000	0.006
Age squared	−0.000	0.000	−0.001***	0.000	−0.000	0.000	−0.001***	0.000	−0.000*	0.000	−0.000***	0.000
Constant	−0.106	0.222	0.092	0.223	−0.245	0.247	−0.364	0.247	−0.134	0.176	1.300***	0.186
F test for quadratic age	2.609		867.253***		5.532*		798.686***		7.198**		1340.141***	
F test for excluded instruments	71.362***		1144.089***		79.971***		972.495***		124.382***		1174.868***	
Weak identification test	12.579***		201.592***		10.948***		172.862***		14.441***		77.021***	
N. obs.	58342				47807				68151			
N. ind.	11415				9171				14556			

Notes: 1. Linear probability model with fixed effects. 2. P: Married or unmarried partner. 3. ***, **, * indicate statistical significance at the 0.01, 0.05, 0.10 levels, respectively. 4. Weak identification test tests the null hypothesis that the particular endogenous regressor alone is not identified. The test is based on the Sanderson-Windmeijer F statistic. 5. Standard errors and test statistics are robust to heteroskedasticity and clustering on panel groups.

Table 11: Results for IV-RE model explaining BMI

	BMI	
	Coef.	S. E.
Part-time	−3.460***‡	1.076
Full-time	−1.106***	0.282
Age	0.559***	0.055
Age squared	−0.004***	0.000
Constant	11.357***	1.421
End. test		
Ove. test	0.107	
F test for work status	15.458***	
F test for quadratic age	154.356***	
N. obs.	67382	
N. ind.	21128	
N. obs.	65865	
N. ind.	13001	

Notes: 1. Linear model with instrumental variables and random effects. 2. The model employs six instrumental variables consisting of the retirement eligibility age indicators for the respondent and the partner. 3. BMI takes values from 10.9 to 82.7. Higher values indicate increasing body weight. 4. ‡ indicates that equality of the coefficients of part-time and full-time is rejected at the 0.05 level. 5. Endogeneity test (denoted as End. test) tests the null hypothesis that the variables 'part-time' and 'full-time' are exogenous. The test is based on the C statistic. Overidentification test (denoted as Ove. test) tests the null hypothesis that all instruments are uncorrelated with the unobserved error. The test is based on the Hansen J statistic. 7. Standard errors and test statistics are robust to heteroskedasticity and clustering on panel groups. 8. ***, **, * indicate statistical significance at the 0.01, 0.05, 0.10 levels, respectively.

Table 12: Results for IV-RE models explaining BMI using different instrument sets

	Model 1A		Model 1B		Model 2A		Model 2B		Model 3A		Model 3B	
	Coef.	S. E.	Coef.	S. E.	Coef.	S. E.	Coef.	S. E.	Coef.	S. E.	Coef.	S. E.
Part-time	-4.029^{***}‡	0.645	-4.947^{***}‡	0.648	-3.031^{***}‡	0.703	-2.812^{***}‡	0.760	-3.154^{***}‡	0.848	-2.292	1.454
Full-time	-1.184^{***}	0.249	-1.365^{***}	0.348	-1.013^{***}	0.267	-0.904^{***}	0.333	-1.055^{***}	0.261	-0.912^{**}	0.397
Age	0.593^{***}	0.055	0.637^{***}	0.055	0.555^{***}	0.061	0.509^{***}	0.059	0.549^{***}	0.048	0.520^{***}	0.060
Age squared	-0.005^{***}	0.000	-0.005^{***}	0.000	-0.004^{***}	0.001	-0.004^{***}	0.001	-0.004^{***}	0.000	-0.004^{***}	0.001
Constant	10.900^{***}	1.469	10.042^{***}	1.555	11.653^{***}	1.599	12.924^{***}	1.570	11.507^{***}	1.326	12.019^{***}	1.462
End. test												
Ove. test	3.189		0.170		0.923		0.376		0.574		0.128	
F test for work status	40.268^{***}		58.972^{***}		19.931^{***}		14.748^{***}		17.424^{***}		5.434^{*}	
F test for quadratic age	168.868^{***}		154.904^{***}		150.369^{***}		114.117^{***}		172.034^{***}		130.749^{***}	
N. obs.	57638		57638		47197		47197		67382		67382	
N. ind.	21128		21128		21128		21128		21128		21128	

Notes: 1. Linear model with instrumental variables and fixed effects. 2. The model employs six instrumental variables consisting of the retirement eligibility age indicators for the respondent and the partner. 3. BMI takes values from 10.9 to 82.7. Higher values indicate increasing body weight. 4. ‡ indicates that equality of the coefficients of part-time and full-time is rejected at the 0.05 level. 5. Endogeneity test (denoted as End. test) tests the null hypothesis that the variables 'part-time' and 'full-time' are exogenous. The test is based on the C statistic. Overidentification test (denoted as Ove. test) tests the null hypothesis that all instruments are uncorrelated with the unobserved error. The test is based on the Hansen J statistic. 7. Standard errors and test statistics are robust to heteroskedasticity and clustering on panel groups. 8. ***, **, * indicate statistical significance at the 0.01, 0.05, 0.10 levels, respectively. 9. Model 1A uses a total of seven instruments: the retirement age indicators of the respondent, the same indicators for the partner, and the indicator of self-employment status. Model 1B uses a total of three instruments: the indicator of whether the respondent is between the normal retirement age and age 70, the same indicator for the partner, and the indicator of self-employment status. Model 2A uses a total of seven instruments: the retirement age indicators of the respondent, the same indicators for the partner, and the indicator of able to reduce paid hours. Model 2B uses a total of three instruments: the indicator of whether the respondent is between the normal retirement age and age 70, the same indicator for the partner, and the indicator of able to reduce paid hours. Model 3A uses a total of seven instruments: the retirement age indicators of the respondent, the same indicators for the partner, and the indicator of male. Model 3B uses a total of three instruments: the indicator of whether the respondent is between the normal retirement age and age 70, the same indicator for the partner, and the indicator of male.

Econometric model

Our econometric model makes use of instrumental variables to circumvent the endogeneity of hours worked, and exploits the panel nature of the data to allow for fixed effects that control for unobserved individual heterogeneity. To show the extent to which the endogeneity of hours worked and individual heterogeneity affect the estimated coefficients, Table 13 presents the results using three alternative models. In the first model, we do not exploit the panel dimension of the data, and do not control for the endogeneity of hours worked; rather we follow a pooled OLS estimation. In the second model, we do not allow for endogeneity of hours worked, but exploit the panel dimension of the data, and follow a panel FE estimation which uses the within group estimator (the within group transformation followed by OLS). In the third model, we do not exploit the panel dimension of the data, but allow for endogeneity of hours worked, and follow a pooled IV estimation that uses the two-stage least squares estimator. The baseline panel IV-FE model, reproduced in the right most panel of the table, uses the two-stage least squares estimator after the within group transformation.

A first finding is that the signs as well as the magnitudes of the estimated effects change when we control for the endogeneity of hours worked. We also reject the null hypothesis that the variables 'part-time' and 'full-time' are exogenous, regardless of if we control for unobserved individual heterogeneity. These provide evidence that BMI is endogenous to the number of hours worked. A second finding is that the signs, the magnitudes, as well as the statistical significance of the estimated effects change when we control for unobserved individual heterogeneity. This suggests that individuals have BMI related unobserved characteristics that are also correlated with their labor market behavior. Overall, these results suggest that controlling for the endogeneity of hours worked and individual heterogeneity are both essential in the analysis of the effect of the number of hours worked on body weight among the elderly worker.

Table 13: Robustness check on the econometric model

	BMI							
	Pooled OLS		FE		Pooled IV		FE-IV	
	Coef.	S. E.	Coef.	S. E.	Coef.	S. E.	Coef.	S. E.
Part-time	-0.932^{***}	‡0.056	-0.027	0.042	8.421^{***}	‡3.194	-3.021^{***}	‡1.003
Full-time	-0.541^{***}	0.051	-0.034	0.039	0.744	0.676	-0.846^{***}	0.275
End. test					16.719^{***}		13.813^{***}	
Ove. test					0.452		1.394	

Notes: 1. Linear models with or without instrumental variables and fixed effects. 2. The instrumental variable models employ the same six instrumental variables consisting of the retirement eligibility age indicators for the respondent and the partner. 3. BMI takes values from 10.9 to 82.7. Higher values indicate increasing body weight. 4. Standard errors are robust to heteroskedasticity and clustering on panel groups. However, the latter correction is not done in the Pooled OLS and Pooled IV regressions so that the FE and IV-FE regressions fully reflect the effect of exploiting the panel dimension of the data. 5. ‡ indicates that equality of the coefficients of part-time and full-time is rejected at the 0.05 level. 6. Endogeneity test (denoted as End. test) tests the null hypothesis that the variables 'part-time' and 'full-time' are exogenous. The test is based on the C statistic. Overidentification test (denoted as Ove. test) tests the null hypothesis that all instruments are uncorrelated with the unobserved error. The test is based on the Hansen J statistic. Both tests are robust to heteroskedasticity and clustering on panel groups. 7. ***, **, * indicate statistical significance at the 0.01, 0.05, 0.10 levels, respectively.

Age specification

Our econometric model has allowed for a quadratic function of age to capture the possibly nonlinear changes in hours worked in the first-stage regression, and in the BMI in the second-stage regression. Here we analyze the changes in the coefficient estimates and the specification test results in the first-stage and second-stage regressions when we employ linear and cubic functions of age.

Tables 14 and 15 present the results from the first-stage regressions of part-time and full-time work when we employ linear and cubic functions of age. In both tables we reproduce the results for the quadratic function of age to ease comparison. A main finding is that, in both regressions of part-time and full-time work, the magnitudes of the coefficient estimates of the eligibility ages of the respondent decrease substantially when we control for a cubic function of age, compared to when we control for a quadratic function of age. This is obviously because the eligibility ages lose explanatory power as we allow for greater flexibility in the continuous function of age. Another finding is that the coefficient estimate of the cubic age term is virtually zero, although significant. The magnitudes or the significance of the coefficient estimates of the eligibility ages of the respondent also decrease when we employ a linear function of age in the regression of part-time work. We conclude that a quadratic function of age captures the nonlinear changes in hours worked well, while it allows the eligibility ages to preserve their predictive power.

Table 16 presents the results from the second-stage regressions of the BMI when we employ linear and cubic functions of age. We also reproduce the results for the quadratic function of age. There are two main findings. First, the effect of working part-time is slightly smaller and less significant, and the effect of working full-time is smaller and becomes insignificant when we employ a cubic function of age, compared to when we employ a quadratic function of age. The effect of working full-time also becomes insignificant. These results are apparently due to the fact that the predictive power of the retirement eligibility ages has decreased as we allow for a very flexible cubic function of age. The table also shows that the individual effect of the cubic age term is virtually zero and is not significant at the 0.05 level.

Second, the J statistic for testing the exogeneity of the instruments gains substantial power when we employ a linear function of age in almost all regressions, compared to when we employ quadratic and cubic functions of age. A potential reason is that in the second-stage regressions employing a linear function of age, the retirement eligibility ages become correlated with the error term as we leave the explanatory power of the quadratic and cubic age terms to the error term. These results support the use of a quadratic age function in the baseline analysis.

Table 14: Robustness check for the first-stage FE model explaining part-time work status

	Part-time					
	Linear age		Quadratic age		Cubic age	
	Coef.	S. E.	Coef.	S. E.	Coef.	S. E.
Bet. early and normal ret. age	0.034***	0.005	0.036***	0.005	0.024***	0.006
Bet. normal ret. age and age 70	0.037***	0.008	0.045***	0.008	0.023**	0.010
Over age 70	0.011	0.011	0.031***	0.011	0.013	0.013
Bet. early and nor. ret. age (P)	−0.011**	0.005	−0.011**	0.006	−0.012**	0.006
Bet. nor. ret. age and age 70 (P)	−0.041***	0.008	−0.040***	0.008	−0.042***	0.008
Over age 70 (P)	−0.087***	0.012	−0.084***	0.012	−0.085***	0.012
Age	0.002***	0.001	0.016**	0.006	−0.263***	0.079
Age squared			−0.000**	0.000	0.004***	0.001
Age cubed					−0.000***	0.000
Constant	0.058	0.039	−0.343*	0.189	5.352***	1.624
F test for quadratic age			5.331***			
F test for cubic age					8.579***	
F test for excluded instruments	27.771***		18.655***		12.741***	
Weak identification test	28.367***		12.681***		13.067***	
N. obs.	68151					
N. ind.	14556					

Notes: 1. Linear probability model with fixed effects. 2. P: Married or unmarried partner. 3. ***, **, * indicate statistical significance at the 0.01, 0.05, 0.10 levels, respectively. 4. Weak identification test tests the null hypothesis that the particular endogenous regressor alone is not identified. The test is based on the Sanderson-Windmeijer F statistic. 5. Standard errors and test statistics are robust to heteroskedasticity and clustering on panel groups.

Table 15: Robustness check for the first-stage FE model explaining full-time work status

	Full-time					
	Linear age		Quadratic age		Cubic age	
	Coef.	S. E.	Coef.	S. E.	Coef.	S. E.
Bet. early and normal ret. age	−0.166***	0.007	−0.162***	0.007	−0.107***	0.007
Bet. normal ret. age and age 70	−0.257***	0.010	−0.242***	0.009	−0.146***	0.011
Over age 70	−0.245***	0.013	−0.207***	0.012	−0.127***	0.014
Bet. early and nor. ret. age (P)	−0.027***	0.006	−0.027***	0.006	−0.023***	0.006
Bet. nor. ret. age and age 70 (P)	−0.023**	0.009	−0.021**	0.009	−0.015	0.009
Over age 70 (P)	0.006	0.013	0.012	0.013	0.014	0.013
Age	−0.024***	0.001	0.001	0.007	1.213***	0.085
Age squared			−0.000***	0.000	−0.020***	0.001
Age cubed					0.000***	0.000
Constant	2.105***	0.046	1.354***	0.202	−23.412***	1.759
F-test for quadratic age			542.695***			
F-test for cubic age					385.393***	
F-test for excluded instruments	178.542***		178.274***		49.083***	
Weak identification test	129.182***		37.230***		60.070***	
N. obs.	68151					
N. ind.	14556					

Notes: 1. Linear probability model with fixed effects. 2. P: Married or unmarried partner. 3. ***, **, * indicate statistical significance at the 0.01, 0.05, 0.10 levels, respectively. 4. Weak identification test tests the null hypothesis that the particular endogenous regressor alone is not identified. The test is based on the Sanderson-Windmeijer F statistic. 5. Standard errors and test statistics are robust to heteroskedasticity and clustering on panel groups.

Table 16: Robustness check on the functional form of age for the IV-FE model explaining health outcomes

	BMI					
	Linear age		Quadratic age		Cubic age	
	Coef.	S. E.	Coef.	S. E.	Coef.	S. E.
Part-time	2.468***	0.650	−3.021***	1.003	−2.878***	1.005
Full-time	0.343	0.214	−0.846***	0.275	−0.469	0.409
Age	0.085***	0.009	0.556***	0.054	−0.594	0.875
Age squared			−0.004***	0.000	0.014	0.014
Age cubed					−0.000	0.000
End. test	23.236***		13.813***		10.530***	
Ove. test	51.906***		1.394		1.037	
F test for quadratic age			187.750***			
F test for cubic age					189.465***	
N. obs.	65865					
N. ind.	13001					

Notes: 1. Linear models with instrumental variables and fixed effects. 2. All models employ the same six instrumental variables consisting of the retirement eligibility age indicators for the respondent and the partner. 3. BMI takes values from 10.9 to 82.7. Higher values indicate increasing body weight. 4. ‡ indicates that equality of the coefficients of part-time and full-time is rejected at the 0.05 level. 5. F-test tests the null hypothesis that the coefficients of the age terms are zero. Endogeneity test (denoted as End. test) tests the null hypothesis that the variables 'part-time' and 'full-time' are exogenous. The test is based on the C statistic. Overidentification test (denoted as Ove. test) tests the null hypothesis that all instruments are uncorrelated with the unobserved error. The test is based on the Hansen J statistic. 6. Standard errors and test statistics are robust to heteroskedasticity and clustering on panel groups. 6. ***, **, * indicate statistical significance at the 0.01, 0.05, 0.10 levels, respectively.

Part-time status

As discussed in Section 3.2, in the HRS, working under 35 hours can correspond to two different labor force participation statuses: 'working part-time' as well as 'partly retired'. Table 2 presented the fraction of individuals in the two modes of part-time employment before and after the age at which they become eligible for social security. The fraction of those working part-time decreases, while that of those partly retired increases when individuals become eligible for social security. A potential explanation is that, among those working less than 35 hours, more people report being retired and are therefore categorized as 'partly retired' at older ages.

Here we check if the effect of working under 35 hours in our baseline analysis changes between when respondents are working part-time and when they are partly retired in any given survey year. In particular, we repeat the estimation on two restricted sub-samples of the data. We require those working less than 35 hours in any given survey year to be partly retired in the first sub-sample, and to be working part-time in the second sub-sample.

With respect to the first-stage results, we find that the effects of the retirement ages of the respondent on the probability of working less than 35 hours are significant and positive and larger than those presented in Table 4 in the first sub-sample (part-time retirees), while they are less significant or insignificant and negative and much smaller than those presented in Table 4 in the second sub-sample (part-time workers). On the other hand, the effects of the retirement ages of the partner on the probability of working less than 35 hours are often insignificant and negative and much smaller than those presented in Table 4 in the first sub-sample, while they are significant and negative and somewhat smaller than those presented in Table 4 in the second sub-sample. We find no significant change for the effects on the probability of full-time work.

Table 17 presents the second-stage results from the estimations based on the two sub-samples. The signs, magnitudes, and significance of the coefficient estimates of working less than 35 hours are comparable across the two sub-samples. However, compared to the results using the full sample, the effect of full-time work becomes insignificant in the second sub-sample.

Table 17: Robustness check on the definition of part-time work

	BMI			
	Part-time retiree		Part-time worker	
	Coef.	S. E.	Coef.	S. E.
Part-time	-4.143^{**}	1.628	-3.759^{***}	1.405
Full-time	-1.238^{***}	0.449	-0.119	0.212
End. test	8.251^{**}		11.071^{***}	
Ove. test	2.787		1.848	

Notes: 1. Linear models with instrumental variables and fixed effects. 2. Both models employ the same six instrumental variables consisting of the retirement eligibility age indicators for the respondent and the partner. 3. BMI takes values from 10.9 to 82.7. Higher values indicate increasing body weight. 4. ‡ indicates that equality of the coefficients of part-time and full-time is rejected at the 0.05 level. 5. Endogeneity test (denoted as End. test) tests the null hypothesis that the variables 'part-time' and 'full-time' are exogenous. The test is based on the C statistic. Overidentification test (denoted as Ove. test) tests the null hypothesis that all instruments are uncorrelated with the unobserved error. The test is based on the Hansen J statistic. 6. Standard errors and test statistics are robust to heteroskedasticity and clustering on panel groups. 7. ***, **, * indicate statistical significance at the 0.01, 0.05, 0.10 levels, respectively.

Number of hours worked per week

As discussed in Section 3.2, we define part-time work as working less than 35 hours a week, or as working 35 or more hours a week but less than 36 weeks a year. To distinguish part-time work from full-time work, here we consider two alternative thresholds for the number of hours worked per week, and check whether the baseline results are sensitive to these thresholds. In particular, we consider 30 and 25 hours of work per week as two alternative thresholds. We do not consider changing the threshold for the number of weeks worked per year and always fix it at 36 because there is little variation in the number of weeks worked per year in the sample data (see Figure 1). We find that our results are not sensitive to the changes in the threshold numbers of hours worked week.

Lagged effect of retirement

We have examined the contemporaneous effect of labor market participation and hours worked on the BMI. A concern is that retirement, in comparison to working, may have a lagged rather than a contemporaneous effect on the BMI. That is, the BMI may increase, and hence differ from that of a current worker, but only after a number of years spent in retirement. We check if the contemporaneous effects of part-time and full-time working on the BMI change when we require the comparison group of retired respondents to be retired for at least one year. We find no significant change in the results when compared to the baseline results.

6 Mechanism analysis

In the previous section we have provided empirical evidence that working in old age has a causal effect on body weight for women, and that the effect of working part-time is larger than that of working full-time. Here we investigate the possible mechanisms behind these causal effects. To this purpose, we explore time use data. Analysis of time use data among the elderly serves especially well to this purpose because individuals are subjected to change their time allocation across work and non-work activities when they become partially or fully retired and are therefore exposed to substantial amounts of free time. If time spent on working complements or substitutes the time spent on activities that contribute to gaining or losing body weight, then changes in the time spent on working due to partial or full retirement should alter body weight.

Figures 5–7 present univariate nonparametric regressions of the time spent on different types of activities (in hours per day) by the age of the respondent, allowing for jumps at the retirement eligibility ages. For men (left panels in the figures), there are obvious discontinuities at the cutoff ages in the times spent on housework, purchasing prepared food, primary eating, screen time, and sleeping. The jumps are most pronounced and often statistically significant for primary eating, screen time, and sleeping.[1] For women, we observe similar discontinuities for primary eating, screen time, and sleeping as for men. This suggests that individuals trade off the time spent working mainly against the time spent on primary eating, screen, and sleeping when they are able to do this due to retirement. On the other hand, we observe notably different amounts of time spent on a number of activities between men and women. On average, at almost any given age, men spend about 10 minutes more on exercise, 15 minutes less on food and drink preparation, 40 minutes less on housework, and 1 hour more on screen.

Figure 8 presents the time spent on different types of activities as fractions of the time spent on all activities between 4 a.m. on the day before the interview until 4 a.m. on the day of

[1] Primary eating indicates eating and drinking as a primary activity. Secondary eating indicates eating and drinking while primarily performing another activity. Screen time indicates time spent on watching television and using computer for non-work related reasons.

the interview for full-time workers, part-time workers, and retirees, by gender groups. Notable patterns are the following. In line with Figures 5–7, compared to when retired, when working part-time or full-time both men and women spend substantially less time on screen. This shows that when individuals retire, they trade off a substantial fraction of their time spent working with time spent on screen rather than with time spent on other activities. Furthermore, men spend substantially more time on screen than women, regardless of how many hours they work. Another notable pattern is that, compared to when working full-time, when working part-time men spend substantially more time on screen than women.

Using regression analysis, Tables 18 and 19 formalise the differences in time use on non-work related activities between individuals working different number of hours, and between men and women observed in Figures 5–8. Table 18 presents the results from the estimation of separate regressions for each of eleven activities. The activities are selected based on the time spent the most. In each regression we control for dummies for working part-time and full-time and a set of background characteristics. Being retired is considered as the base category for these dummies. The main finding is that when working part-time and full-time, compared to when being retired, both men and women spend less time on food and drink preparation, sleeping, exercise, screen, and own medical care. The most pronounced effect is observed for screen time.

In Table 19 we estimate the same regressions as in Table 18 except that we control for dummies for working part-time and being retired, and consider working full-time as the base category for these dummies. The main finding is that, relative to men, when working part-time, compared to when working full-time, women spend less time on sleeping, screen, and purchasing prepared food, and more time on food and drink preparation, grocery, household activities, and exercise. These results suggest that, relative to men, women more often engage in physically demanding activities when they are working part-time compared to when they working full-time.

To investigate the channels through which working part-time and full-time affects the BMI, we analyse how working part-time and full-time affect the BMI when we do not and when we control for time spent on non-work related activities in multivariate regression analysis. If working part-time and full-time affect the BMI through their interaction with non-work related activities, ignoring time use on non-work related activities as correlates in the regression of the BMI on working part-time and full-time should result in biased estimates of working part-time and full-time. Table 20 presents results from the estimation of a series of linear models explaining the BMI with dummies on working part-time and full-time where being retired is treated as the base category for these dummies. The differences are that the linear model presented in the first row includes no variable on time use. The models presented in the second until the last row include at a time an additional variable on time use. The model presented in the last row includes all variables on time use. All models include a set of other background characteristics.[2]

The main finding is that both working part-time and full-time are significant for both men and women when we do not control for time use on an activity. However, while the effects remain significant when we control for time spent on given activities, they often become insignificant when we control for time spent on screen. In particular, working full-time becomes insignificant

[2] Unlike in our regression analysis based on the HRS data, here we do not take an instrumental variables approach. When we consider the retirement eligibility ages as instruments for working part-time and full-time, we find no statistical evidence that hours worked is endogenous: the null hypothesis that the variables 'part-time' and 'full-time' are exogenous is not rejected. A possible explanation is that hours worked is endogenous when unobserved individual heterogeneity is accounted for. Since the ATUS sample is a repeated cross-section of individuals, we are not able to control for unobserved heterogeneity. When we treat the HRS sample as a pooled cross-section of individuals, as in Table 13, and estimate separate regressions for men and women, we obtain very similar results for working part-time and full-time as those presented in the first row of Table 20.

for both men and women, and working part-time remains significant for women but not for men. The obvious reason for the insignificant effects is the strong correlation between hours worked and screen time as suggested by Table 18. This correlation, and the fact that screen time is correlated with the BMI, lead to an upward omitted variable bias in the coefficients of part-time and full-time work dummies in the regression where no account of time use is taken (first row of Table 20). On the other hand, the coefficient of working part-time remains significant for women when we control for time spent on screen. This suggests that, for women, working part-time has an idiosyncratic effect on the BMI independent of the other competing non-work related factors that contribute to the BMI, particularly screen time. This finding is in line with the large and significant causal effect of working part-time on the BMI presented in Table 5. We also find that, next to working part-time, purchasing prepared food and exercise are other important factors that determine the BMI among women in old age.

The results for women in the right panel of 4 as well as in Table 5 suggested that part-time workers have a lower BMI than those who are retired and working full-time, and that the difference between part-time workers and those who are retired is larger than that between part-time workers and those who are working full-time. Table 20 presented the effects of working part-time (and full-time) relative to those who are retired. Table 21 presents the effects of working part-time (and being retired) relative to those who are working full-time. The results in these tables confirm the results in Table 5: relative to those who are retired or working full-time, part-time workers have a lower BMI, and the difference between part-time workers and those who are retired is larger than that between part-time workers and those who are working full-time, even when we control for time spent on non-work related activities and other background characteristics. Another finding in Table 21 is that the size of the effect of working part-time becomes larger when we control for time spent on screen, but the size of the bias is not large.

Tables 18 and 19 showed that individuals trade off their working time with time spent on screen when they reduce hours or when they become retired. As Tables Table 20 and Table 21 showed, an important consequence of this trade-off is that working part-time and full-time interact with screen time in their effect on the BMI. This trade-off appears to be important because in terms of the amount of metabolic energy different activities demand, screen time is a least demanding activity. In Figure 9 we present the metabolic energy requirements of different activities in kilocalories, based on the ATUS data and the Compendium of Physical Activities which was developed to classify physical activities by rate of energy expenditure (Ainsworth et al., 1993). The figure shows that screen time requires almost the same amount of metabolic energy as sleeping. This implies that whether and how much individuals substitute their free time with screen time is important because screen time presents itself as a potential means of physical inactivity and a contributor to body weight.

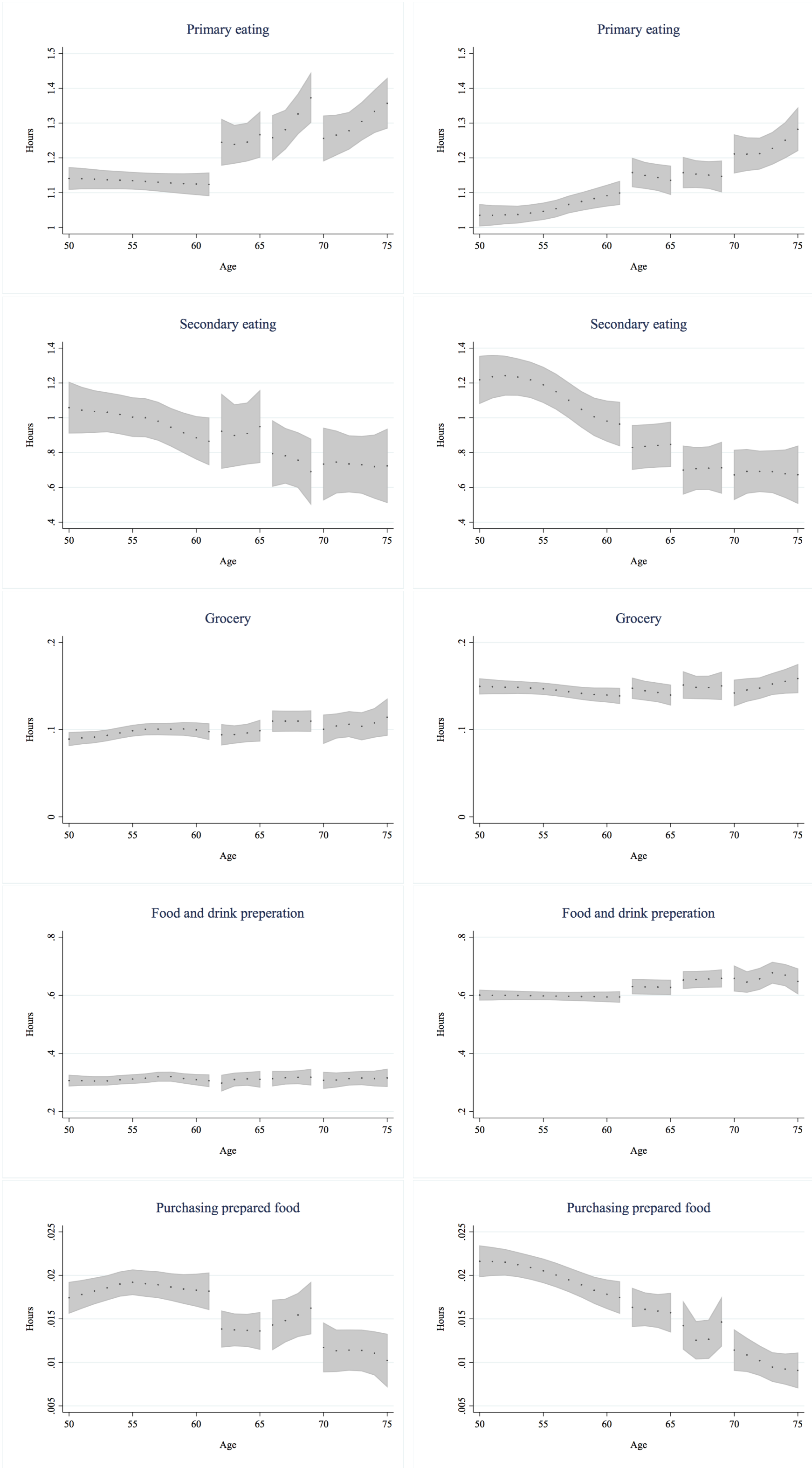

Figure 5: Time use by activity (hours per day) and age of the respondent, allowing for jumps at the pension eligibility ages, for men (left panel) and women (right panel). Kernel smoothed local polynomials and 95% CI around them.

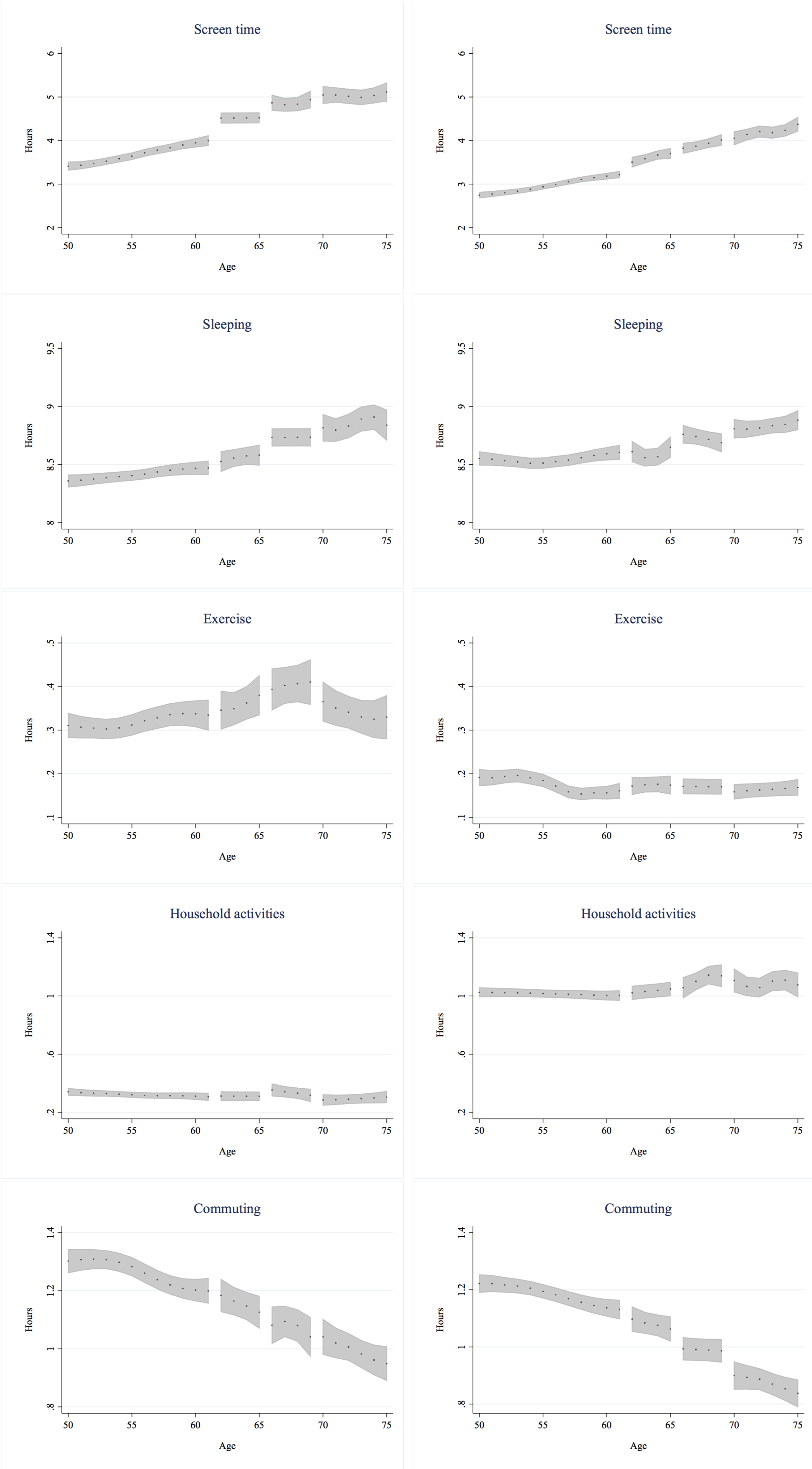

Figure 6: Time use by activity (hours per day) and age of the respondent, allowing for jumps at the pension eligibility ages, for men (left panel) and women (right panel). Kernel smoothed local polynomials and 95% CI around them.

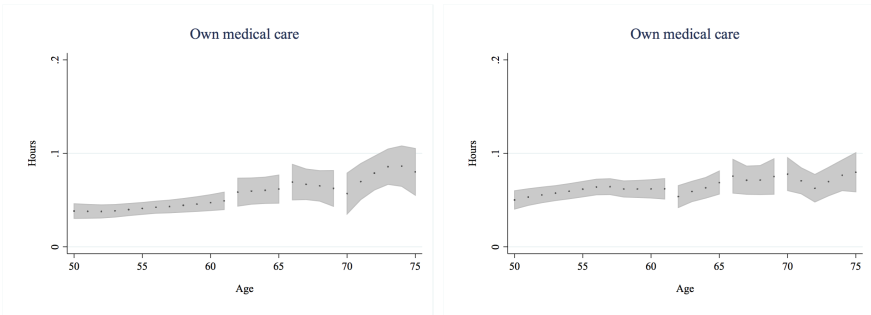

Figure 7: Time use by activity (hours per day) and age of the respondent, allowing for jumps at the pension eligibility ages, for men (left panel) and women (right panel). Kernel smoothed local polynomials and 95% CI around them.

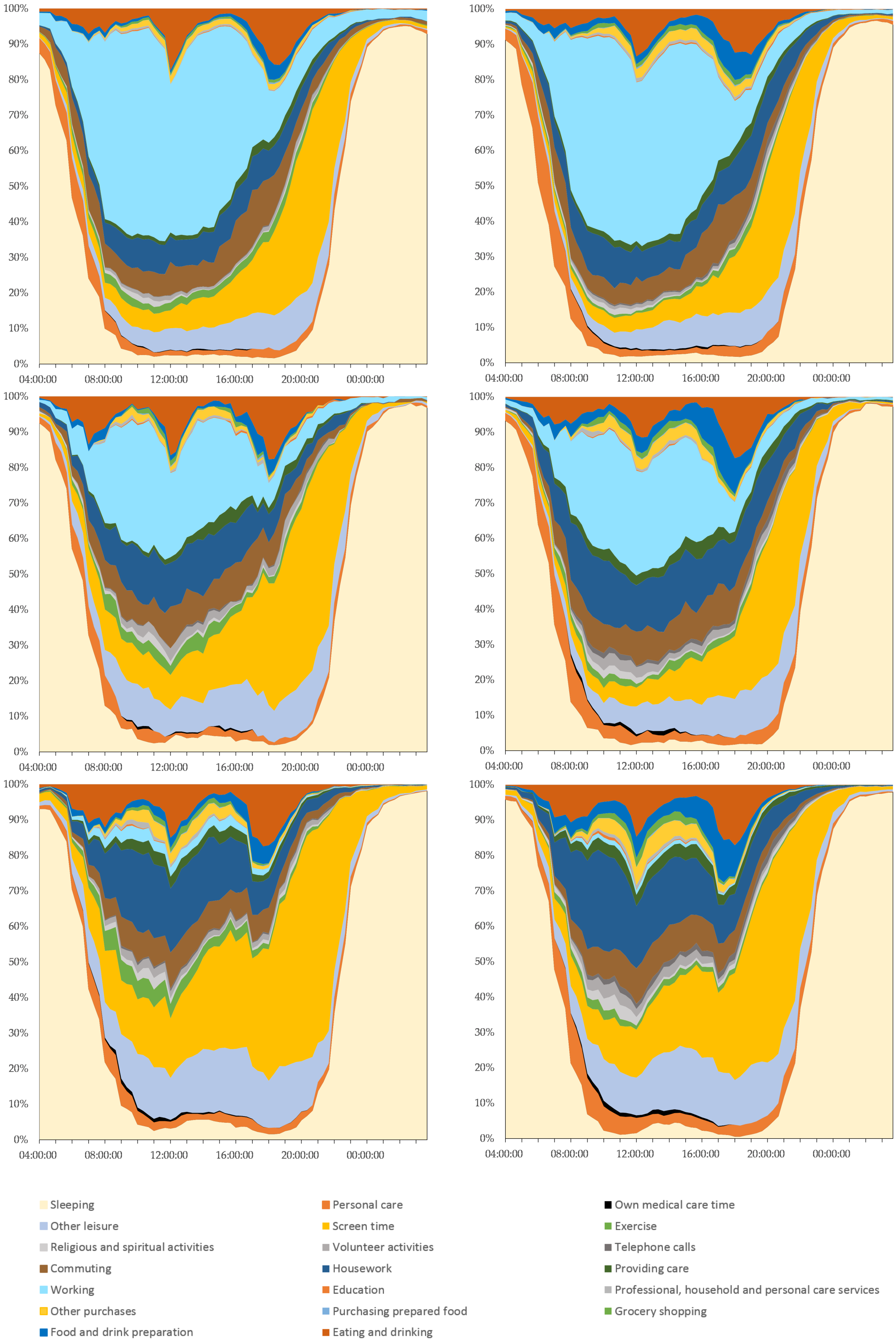

Figure 8: Time spent on different types of activities as fractions of the time spent on all activities between 4 a.m. on the day before the interview until 4 a.m. on the day of the interview among full-time workers (top panel), part-time workers (middle panel), and retirees (bottom panel) for men (left panel) and women (right panel).

Table 18: Effects of working part-time and full-time on time use on a given activity

	Men				Women			
	Part-time		Full-time		Part-time		Full-time	
	Coef.	S. E.	Coef.	S. E.	Coef.	S. E.	Coef.	S. E.
Primary eating	-0.066	0.042	-0.097^{***}	0.034	-0.059^{*}	0.034	-0.072^{***}	0.026
Secondary eating	-0.172	0.169	-0.275	0.203	0.056	0.110	0.095	0.108
Food and drink preparation	-0.085^{***}	0.019	-0.126^{***}	0.013	-0.066^{***}	0.021	-0.177^{***}	0.018
Grocery	-0.013	0.009	-0.028^{***}	0.007	-0.017^{*}	0.009	-0.032^{***}	0.009
Purchasing prepared food	0.002	0.002	0.005^{***}	0.002	-0.003	0.002	0.003	0.002
Sleeping	-0.152^{**}	0.067	-0.622^{***}	0.046	-0.332^{***}	0.042	-0.538^{***}	0.042
Exercise	-0.193^{***}	0.030	-0.233^{***}	0.026	-0.041^{**}	0.016	-0.099^{***}	0.014
Household	-0.051	0.031	-0.138^{***}	0.023	-0.187^{***}	0.036	-0.406^{***}	0.033
Screen time	-1.232^{***}	0.110	-1.959^{***}	0.074	-1.099^{***}	0.064	-1.499^{***}	0.056
Commuting	0.195^{***}	0.044	0.237^{***}	0.031	0.112^{***}	0.029	0.110^{***}	0.027
Own medical care	-0.029^{***}	0.010	-0.042^{***}	0.008	-0.028^{***}	0.010	-0.028^{***}	0.009
N Obs.	22655				27762			

Notes: 1. Linear model explaining time use on a given activity. 2. A given row presents the coefficient estimates from a regression where the dependent variable is time spent on a given activity, and the independent variables are working part-time and full-time. Each regression also includes a constant term, quadratic age terms, dummies for race, high education, marital status, and whether living in a non-metropolitan area. Being retired is treated as the base category for the dummy variables working part-time and full-time. 3. Each variable on time use is measured in hours. 4. Standard errors are calculated using the replicate variance method. 5. ***, **, * indicate statistical significance at the 0.01, 0.05, 0.10 levels, respectively.

Table 19: Effects of working part-time and retirement on time use on a given activity

	Men				Women			
	Part-time		Retirement		Part-time		Retirement	
	Coef.	S. E.	Coef.	S. E.	Coef.	S. E.	Coef.	S. E.
Primary eating	0.031	0.040	0.097***	0.034	0.012	0.029	0.072***	0.026
Secondary eating	0.103	0.170	0.275	0.203	−0.038	0.119	−0.095	0.108
Food and drink preparation	0.041**	0.017	0.126***	0.013	0.111***	0.019	0.177***	0.018
Grocery	0.014	0.009	0.028***	0.007	0.016**	0.008	0.032***	0.009
Purchasing prepared food	−0.003*	0.002	−0.005***	0.002	−0.005***	0.002	−0.003	0.002
Sleeping	0.470***	0.064	0.622***	0.046	0.205***	0.036	0.538***	0.042
Exercise	0.041	0.028	0.233***	0.026	0.058***	0.014	0.099***	0.014
Household	0.087***	0.026	0.138***	0.023	0.219***	0.033	0.406***	0.033
Screen time	0.728***	0.098	1.959***	0.074	0.400***	0.055	1.499***	0.056
Commuting	−0.042	0.044	−0.237***	0.031	0.002	0.026	−0.110***	0.027
Own medical care	0.013	0.009	0.042***	0.008	0.000	0.009	0.028***	0.009
N Obs.	22655				27762			

Notes: 1. Linear model explaining time use on a given activity. 2. A given row presents the coefficient estimates from a regression where the dependent variable is time spent on a given activity, and the independent variables are working part-time and being retired. Each regression also includes a constant term, quadratic age terms, dummies for race, high education, marital status, and whether living in a non-metropolitan area. Working full-time is treated as the base category for the dummy variables working part-time and being retired. 3. Each variable on time use is measured in hours. 4. Standard errors are calculated using the replicate variance method. 5. ***, **, * indicate statistical significance at the 0.01, 0.05, 0.10 levels, respectively.

Table 20: Linear model explaining BMI with working part-time, full-time, and with and without time use on non-work related activities

	BMI											
	Men						Women					
	Part-time		Full-time		Activity		Part-time		Full-time		Activity	
	Coef.	S. E.	Coef.	S. E.	Coef.	S. E.	Coef.	S. E.	Coef.	S. E.	Coef.	S. E.
	−0.404*	0.221	−0.491***	0.186			−0.911***‡	0.233	−0.444**	0.215		
Primary eating	−0.422**	0.220	−0.520***	0.184	−0.290***	0.076	−0.925***‡	0.229	−0.461**	0.213	−0.278***	0.098
Secondary eating	−0.428*	0.220	−0.511***	0.185	0.012	0.019	−0.899***‡	0.232	−0.427**	0.215	0.018	0.029
Food preparation	−0.430*	0.221	−0.517***	0.186	−0.309***	0.109	−0.909***‡	0.234	−0.488**	0.216	−0.289***	0.083
Grocery shopping	−0.403*	0.221	−0.490***	0.185	0.057	0.208	−0.902***‡	0.231	−0.447**	0.214	−0.432**	0.203
Purchasing prepared food	−0.406*	0.221	−0.500***	0.186	2.047**	0.979	−0.893***‡	0.233	−0.441**	0.214	2.194**	1.047
Sleeping	−0.396*	0.220	−0.462**	0.186	0.043	0.035	−0.865***‡	0.231	−0.380*	0.216	0.130***	0.037
Exercise	−0.450**	0.217	−0.550***	0.184	−0.261***	0.051	−0.928***	0.232	−0.534**	0.215	−0.735***	0.117
Housework	−0.403*	0.221	−0.498***	0.186	−0.092	0.075	−0.925***‡	0.233	−0.475**	0.215	−0.090**	0.045
Screen time	−0.243	0.221	−0.226	0.189	0.151***	0.022	−0.691***‡	0.228	−0.141	0.210	0.200***	0.029
Commuting	−0.399*	0.220	−0.486***	0.185	−0.022	0.039	−0.909***‡	0.233	−0.442**	0.215	−0.013	0.062
Own medical care time	−0.408*	0.221	−0.496***	0.186	−0.095	0.139	−0.902***‡	0.233	−0.430**	0.215	0.321	0.250
All activities	−0.358	0.220	−0.356	0.191			−0.651***‡	0.224	−0.205	0.213		
N obs.	6310						7948					

Notes: 1. Linear model explaining BMI. 2. BMI takes values from 11.6 to 76.2. Each variable on time use is measured in hours. 3. The first row presents results from a regression which includes no variable on time use. The regressions presented in the second until the penultimate row include at a time an additional variable on time use. The last row presents results from a regression which includes all variables on time use. All models include a constant term, quadratic age terms, dummies for race, high education, marital status, and whether living in a non-metropolitan area. Being retired is treated as the base category for the part-time and full-time work dummies. 4. ‡ indicates that equality of the coefficients of part-time and full-time is rejected at the 0.05 level. 5. Standard errors are calculated using the replicate variance method. 6. ***, **, * indicate statistical significance at the 0.01, 0.05, 0.10 levels, respectively.

Table 21: Linear model explaining BMI with working part-time, being retired, and with and without time use on non-work related activities

	BMI											
	Men						Women					
	Part-time		Retired		Activity		Part-time		Retired		Activity	
	Coef.	S. E.	Coef.	S. E.	Coef.	S. E.	Coef.	S. E.	Coef.	S. E.	Coef.	S. E.
	0.087	0.213	0.491^{***}	0.185			-0.466^{**}‡	0.214	0.444^{**}	0.215		
Primary eating	0.097	0.213	0.520^{***}	0.184	-0.290^{***}	0.076	-0.463^{**}‡	0.213	0.461^{**}	0.213	-0.278^{***}	0.098
Secondary eating	0.083	0.213	0.511^{***}	0.185	0.012	0.019	-0.472^{**}‡	0.213	0.427^{**}	0.215	0.018	0.029
Food preparation	0.087	0.214	0.517^{***}	0.186	-0.309^{***}	0.109	-0.420^{**}‡	0.213	0.488^{**}	0.216	-0.289^{***}	0.083
Grocery shopping	0.087	0.213	0.490^{***}	0.185	0.057	0.208	-0.454^{**}‡	0.214	0.447^{**}	0.214	-0.432^{**}	0.203
Purchasing prepared food	0.093	0.214	0.500^{***}	0.186	2.047^{**}	0.979	-0.452^{**}‡	0.213	0.441^{**}	0.214	2.194^{**}	1.047
Sleeping	0.065	0.216	0.462^{***}	0.186	0.043	0.035	-0.484^{**}‡	0.215	0.380^{*}	0.216	0.130^{***}	0.037
Exercise	0.099‡	0.214	0.550^{***}	0.184	-0.261^{***}	0.051	-0.393^{*}‡	0.217	0.534^{**}	0.215	-0.735^{***}	0.117
Housework	0.095	0.213	0.498^{***}	0.186	-0.092	0.075	-0.449^{**}‡	0.212	0.475^{**}	0.215	-0.090^{**}	0.045
Screen time	0.017	0.207	0.226	0.189	0.151^{***}	0.022	-0.549^{**}‡	0.212	0.141	0.210	0.200^{***}	0.029
Commuting	0.086	0.213	0.486^{***}	0.185	-0.022	0.039	-0.466^{**}‡	0.214	0.442^{**}	0.215	-0.013	0.062
Own medical care time	0.088	0.213	0.496^{***}	0.186	-0.095	0.139	-0.472^{**}‡	0.214	0.430^{**}	0.215	0.321	0.250
All activities	0.001	0.212	0.356^{*}	0.190			-0.446^{**}‡	0.216	0.204	0.212		
N obs.	6310						7948					

Notes: 1. Linear model explaining BMI. 2. BMI takes values from 11.6 to 76.2. Each variable on time use is measured in hours. 3. The first row presents results from a regression which includes no variable on time use. The regressions presented in the second until the penultimate row include at a time an additional variable on time use. The last row presents results from a regression which includes all variables on time use. All models include a constant term, quadratic age terms, dummies for race, high education, marital status, and whether living in a non-metropolitan area. Working full-time is treated as the base category for the part-time work and retirement dummies. 4. ‡ indicates that equality of the coefficients of part-time and full-time is rejected at the 0.05 level. 5. Standard errors are calculated using the replicate variance method. 6. ***, **, * indicate statistical significance at the 0.01, 0.05, 0.10 levels, respectively.

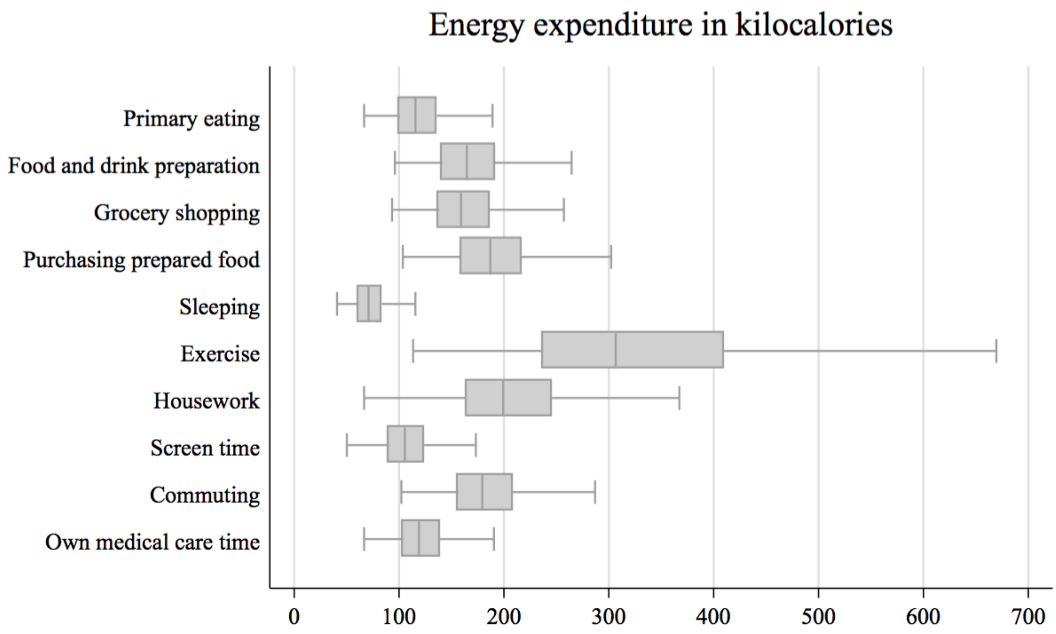

Figure 9: Box plot of energy expenditure in kilocalories for select activities.

7 Conclusion

We analyzed the causal effects of working part-time and full-time on the BMI of US residents between the ages of 50 and 75, controlling for unobserved individual effects and potential endogeneity of labor supply. The two main findings are the following. First, relative to the retired workers, part-time and full-time workers have a much lower body weight. This effect is robust across different specifications and a number of socio-economic groups but it is peculiar to women. Considering that almost 70 percent of our sample consists of individuals who are overweight or obese, promoting part-time work among older workers might be important as those who are fully retired appear to be much more prone to be overweight or obese, and perhaps also prone to the related diseases, such as diabetes or heart attacks. In this respect, working part-time may also help to limit the increasing burden of obesity on medical expenditures (Cawley and Meyerhoefer, 2012).

Second, the effect of working on the BMI is more pronounced for part-time workers than for full-time workers. This result suggests that the effect of the number of work hours on the BMI is not linear in old age.

Analysis of behavioral data shows that when women work part-time, they spend much less time on watching television and sleeping compared to men. In fact, among other activities, these two activities demand the least amount of metabolic energy. Consequently, part-time working women are much less prone to weight gain in old age.

There are a number of potential avenues for future research. We have compared the BMI of the individuals who are working part-time or full-time with those of the individuals who are fully retired at any given survey wave. In this comparison, we did not require individuals to make transitions from or into any work status. We also did not impose any restriction on the labor market history of part-time workers. Some of the part-time workers could have already been part-time workers in the previous years, while others could have reduced working hours from full-time as part of a gradual retirement plan. From a policy perspective, it seems interesting to investigate the BMI outcomes and behavior of the latter group of individuals to understand if offering gradual retirement plans could improve older worker's health by means of a lower BMI as retirement ages continue to raise.

It might be worthwhile to distinguish between the effects of voluntary and involuntary retirement, since it has been shown that these transitions have different effects on the way in which a person experiences retirement, and therefore possibly also on the BMI (van Solinge and Henkens, 2007).

Finally, it might be useful to consider additional measures of health, or other longitudinal datasets in other countries to investigate further the differences between the effects of part-time and full-time work on health.

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